****

**Melodisation of Data:**

**A musical user interface for real-time data exploration and analysis**

**Melo-D**

**Abstract:**

Melo-D will develop interfaces that allow users to explore large datasets through listening to melodic interpretations. We hypothesize that if abstract data sets are associated with musical themes and if combinations of musical traits (such as rhythm, meter, contour, tempo) are associated with patterns of variability in this data, we can develop a new kind of a “musical interface” to these data sets. Listeners will be able to listen as a background task with comparatively little effort, while still being able to detect significant anomalies or changes in the data stream over a longer period of time.

Today, data visualization is a common method for allowing users to interpret and understand information. The visual system, however, as well as current data sonification methods, uses only a subset of the brain’s processing capability, forcing the user to pay attention and therefore imposes a high cognitive load.

We challenge current thinking, which typically associates vision with rational thinking and music with entertainment, by combining the analytical and rational with the aesthetic to usurp the dominance of visual information, and demonstrate that melodic interpretation is an untapped latent skill that can be put to serious use. By using knowledge about the artistic experience we will generate musical interpretations of data that convey information to users, allowing them to draw conclusions or make informed decisions.

The Melo-D consortium consists of musicians and experts in digital music, computer science, physics and human-machine interaction. We aim at developing methods and models for melodisation of three example domains (fish abundance, urban awareness and fluid dynamics) and through user validation identify melodisation approaches that are generally applicable.

**1. Scientific and/or technical quality**

**1.1 Targeted breakthrough and its relevance towards a long-term vision**

Melo-D aims to develop a new way of representing complex data. It is motivated by the difficulties users have in perceiving and capturing the essential features in data if it represents difficult concepts, comes in large volumes, is complex, inconsistent or uncertain, and/or when there is a time constraint, e.g., surveillance data or environmental monitoring. Users need tools to help them understand what is in a data collection and detect significant changes, whether in existing (large) collections of data or in real-time data capture streams.

**Melo-D will develop interfaces that allow users to explore large datasets through listening to melodic interpretations.** We will construct human-interpretable melodic representations of these data sets and investigate to what extent they enable users to carry out certain tasks more effectively, or enable new tasks that are currently not possible.

Experimental brain research demonstrates that listening to music involves nearly all parts of the brain, not just those dedicated to analytical thinking. Brain activity during listening to music is also very different from brain activity when simply listening to sound that is not recognizable as music. People, even those not trained as musicians, are surprisingly good at memorizing and recognizing melodic progression and variations of the same piece of music and are better when compared to the ability of the same people to analyze and interpret abstract data.

We therefore hypothesize that if abstract data sets (such as the results of scientific measurements, security surveillance, traffic conditions, weather predictions, or stock exchange fluctuations) could be associated with musical themes and the variables describing the music (such as rhythm, meter, contour, tempo) can be associated with variability in this data, we can develop a new kind of a musical interface to these data sets. Listeners would be able to **listen as a background task** yet, with comparatively little effort, detect significant anomalies or changes in the data stream over a longer period of time.

Currently, visualization is the most common form of data representation by far, but it is not clear if this is because of underlying human perceptual capabilities or because of the technological limitations that humans have been historically restricted to by two revolutions in information storage and retrieval, that is, the invention of paper and printing. While the human visual system is able to deal with a high data bandwidth, it does not make use of all the processing available in the brain. Other senses, such as tactile and auditory, can also contribute to creating a multi-modal sensing system. Very often, however, the visual channel remains dominant. Our goal is to investigate the degree to which **the auditory channel can be used for higher-level goals of interpreting and analysing (large and streaming) datasets**. The breakthrough required is to understand which aspects of data can be modeled and how these can be rendered as (combinations of) aesthetically appealing melodic renditions. These can then be used to enhance established visual methods of data interpretation and analysis.

We challenge the assumptions that have developed through becoming an intensely visually oriented society, where meaningful use of sound is not typically considered in the educational curriculum. Visual images and symbolic character sets form the basis of cultural information memories, where books established this “supremacy” of the written word. “Serious” information is associated with words, diagrams and data sets, whereas music, song and dance are more often associated with art and entertainment. Forays of exploration into combining sonification with data sets have often been conducted as an artistic rather than a scientific endeavour.

**We will combine the serious with the aesthetic to challenge the dominance of visual information, and demonstrate that melodic interpretation is an untapped latent skill that can be put to serious use.**

To investigate the effectiveness of melodic interpretation, we select the task of interpreting large datasets – a task that is becoming more and more prevalent in many of the sciences and increasingly in the humanities, as more and larger datasets are becoming available online. Our hypothesis is, just as when (most) users listen to a symphony they are unable to specify the notes being played but have a general idea about the progression of the theme and its variations, users should be able to gain a holistic perception of the dataset and be able to explore it initially in coarse steps or to get a general impression. We will demonstrate that **musical interpretations of the data can convey useful information to users, are found aesthetically pleasing** and are not perceived as boring or repetitive and fatiguing even after listening for an extended period of time.

Initially, we will explore specific real-world scenarios of users wishing to interpret data sets, investigate potential ways of creating melodic interpretations and then evaluate to what extent these are of real help to users. Users will be able to explore aspects of the data they are interested in, for example, by quickly “locating” a portion of the dataset that they wish to investigate further or detect significant anomalies.

We will **identify data analysis tasks** in the context of a specified dataset that can be carried out by users visually. The initial target is then to create a melodic rendition of the data that would allow users to interpret what we already know to be in the data. This would take the form of melodic mockups based on available datasets. An intermediate target is to **establish models of data characteristics and melodic combinations** that allow us to construct melodic renditions with which users can carry out known analysis tasks. A final target is to construct an environment in which not only known analysis tasks can be carried out, but also new analyses that the domain users were not otherwise able to do.

The inherent risks are that the appropriate data characteristics that are able to both **represent the meaningful aspects of the data while at the same time allowing the creation of aesthetically acceptable music** will be difficult to specify. It is precisely this challenge we intend to address.

In the short term we expect there to be a relatively large learning curve, while users become accustomed to listening to, rather than looking at, data interpretations. We believe, however, that the investment will be worthwhile in specific cases where users have a prolonged need for interpreting data sources, for example, with data that changes relatively slowly, or where very large amounts of data are involved. Just as it requires years to learn to read and write, it may require an extended period of time to master the tools, and the returns need to be higher than the investment.

**1.2 Novelty and foundational character**

Work to date in data sonification, almost without exception, takes data variables and maps them to simple musical traits such as pitch, volume or rhythm. For example, music is created using water flow or motion of people in a room as input, where the goal is to create an artistic experience. An example of facilitating data interpretation is the sonification of solar wind, where the characteristics of the data are mapped to individual music traits. An example of sonification that moves away from this “one-to-one” mapping uses musical cues to assist debugging in programming. Our goal is to go beyond such methods of sonification by **using knowledge about the artistic experience to generate musical interpretations of data that convey information to users, allowing them to draw conclusions or make informed decisions**.

When fMRI studies are conducted on people listening to music (both musicians and non-musicians), they show that most parts of the brain are active, as opposed to listening to arbitrary, atonal, disorganized sounds, or noise. The latter involves mainly the auditory cortex, which is responsible for perception and analysis of sounds. At the same time, listening to music also activates:

* the hippocampus, associated with memory for music and association of musical experiences and contexts;
* the cerebellum, responsible for movement associated with music, such as foot tapping as well as an emotional reaction to music;
* the nucleus accumbens and amygdala, also enabling an emotional reaction to music;
* the prefrontal cortex, associated with higher level functions, such as planning complex cognitive behaviors and decision making. This allows us to understand the themes in music, their development, references to other musical pieces and their interpretations, develop expectations about how the music will evolve and detect when those expectations get violated.

There is evidence that listening to music involves alternative parts of the brain as opposed to the centres normally associated with a given activity. For example, there are subjects with Williams Syndrome who have severe hand-eye coordination disorders, except when they are playing a musical instrument. Studies have also shown that although our perception of music is dependent on culture and auditory ability, certain musical concepts remain valid across these differences. This is especially true for *pitch progression and relative pitch* that constitutes our basic ability to perceive a melodic structure or theme even when altered by transposition. Relative pitch allows us to recognise the direction of change (up or down) from one note to the next, also known as the contour. An encodable contour not only occurs in a novel sequence of notes, recent evidence indicates that contours can also be perceived in dimensions other than pitch, such as loudness and brightness. A pattern of loudness variation, for instance, can be replicated in a different loudness range, and can be reliably identified as having the same contour. Another interesting feature of pitch is that different sounds with different pitches can be combined to yield a rich array of new sounds. Music takes full advantage of this property, as the presence of multiple simultaneous voices in music is widespread. This capability may be one reason why pitch has such a prominent role in music, relative to many other auditory dimensions. Together with other musical notions such as intervals, chord progression, **consonance and dissonance this** could create a basis for widely usable general concepts for mapping data into musical renditions.

By “melodising” information, Melo-D aims at using the capacity of the whole brain to decrease the cognitive load of the user. The novelty of the proposal is at both the task and the cognitive levels. At the task level, users will be able to explore large data sets more quickly or perceive information in them they were not previously aware of. At the cognitive level, users will use other parts of their brain than those used for visual interpretation, thus allowing different ways of perceiving and interpreting the information they wish to extract from the data.

Data exploration user interfaces tend to focus on improving visualization techniques. An alternative approach is to develop multimodal interfaces, where the visual information is dominant but combined with, e.g., sound or haptics. The purpose of multimodality is to increase the bandwidth of information transfer or allow redundancy between the information channels. Studies show that humans prefer *multimodal interaction* to the monomodal. Given this processing-speed advantage, multimodal interface users start their cognitive process faster, thus, in a similar exposure time they can pay attention to more informative cues and subtle details in the environment and integrate them. In addition to exploiting multimodality of the sensorial system (vision, touch, sound, kinesthetic cues) yet another dimension to data representation is given by affective computing where the perception of information is facilitated by recognizing, expressing, modelling, communicating, and responding to emotions. Melo-D does not contradict these current trends, rather it offers one more possibility, which could be successfully combined with others, to more efficiently use the capacity of the human brain. It also aligns well with the principles of affective computing by creating emotional responses using musical concepts.

The disciplines we propose to combine are those of data analysis, from the scientific perspective, and those of music synthesis, from the artistic perspective. Within the human computer interaction community it is well established that *aesthetically pleasing interfaces* are not just more pleasant for the user, but improve her performance. We will extend this and make an experience of data analysis not just more aesthetically pleasing, but use our knowledge of how to create aesthetically pleasing experiences to be an integral part of the task of understanding and analysing otherwise daunting amounts of data. Also, we do not seek to compete with techniques such as data mining, but rather work synergistically with them and provide audio renditions of their outputs.

**1.3. Specific Contribution to progress of Science and Technology**

Melo-D will develop the following scientific foundations in the area of human-machine interaction and data perception:

* models of properties of datasets that can be used for creating melodic renditions;
* models of suitable combinations of melodic components that can give meaningful renditions;
* models of application domain that allows us to determine beforehand whether domain data is suitable for melodisation;
* a new paradigm for presenting complex, time-varying, uncertain and large datasets using audio renditions;
* methods for personification of data melodisation taking into account user taste, cultural background, musical education, knowledge about existing musical works that help the user to anchor the musical experience to their previous ones;
* algorithms and heuristics for mapping data to musical characteristics;
* software suites for data melodisation;
* methods for evaluation of user data exploration;
* new insights into understanding how people perceive music.

Given that we are attempting to reinvent literacy through the symbolic use of audible rather than visual patterns, the chances of it working immediately are low. The learning curve for our envisioned users may be too high even for our selected scenarios. A means to offset this risk is to “downscale” and select simpler datasets and tasks with which to train users. Early work on “earcons” shows that users can infer meaningful interpretations to synthetic sounds, ensuring at least some baseline from which we can work.

Thus, the greatest risk of Melo-D is associated with the generality of the approach. It is indeed unlikely that we are able to develop a unified theory about how to turn complex datasets into musical renditions that are suitable for every user and every dataset. While we have strong reasons to believe that we can identify relatively general structures of melodic pitch progression using contours, we remain very aware of the issues that arise from variations the datasets themselves and the abilities and preference of our users. To explore this we will aim to develop several alternatives of representing information in musical form, each having advantages and disadvantages. To this end we will work closely with each user group to develop artistically valid and specific compositional responses to each datasets and emergent events, using the preferences and abilities of the users to explore multiple ways to representing these types of data in melodic form.

**1.4 S/T methodology and workplan**

We will take a number of real-world data sources and associated user tasks and use these for exploring suitable types of melodic interpretations. We provide three candidate scenarios here. The types of data and their associated tasks are sufficiently different so that generalisations can be made to methods that are likely to work for other domains.

**Monitoring fluid dynamics**

Fluids are complex physical phenomena and many different methods and variables are used to investigate and analyze flows. Experimental data is gathered by monitoring the flow and later analyzing the flow particles motion. The variables used to describe the flow range from simple physical concepts such as instantaneous speed of a particle to higher-level concepts such as vorticity, periodicity, dynamic viscosity and Reynolds number. Within Melo-D we would experiment with associating these physical quantities with musical building blocks, either directly or in combination, to assist users in **understanding the flow phenomena and relevant changes**.

**Urban soundscapes**

Cities are hybrid spaces consisting of physical places, social structures and an ‘invisible’ layer of data streams that are generated by sensors, devices and monitoring systems as people move and interact within them. These invisible data streams, if made accessible, perceptible and usable for human users, can contribute to carrying out current activities or inspiring new activities. Within Melo-D we would investigate how real-time local information contained in the data streams could be used, for example, to **augment the experience of a user moving through the city** by enabling interaction, such as navigation. Alternatively, remote observers could compare different locations, or detect anomalies through interactive soundscapes.

**Estimating changes in fish populations**

Videos of fish activity on coral reefs can be used by marine biologists to analyse the changes in abundance of fish populations over periods of time. Video is compressed real-time before being stored in a growing database of potential fish detections. Investigations of the data can **produce hypotheses on the increase or decline of the fish populations**, but the conclusions can only be based on understanding the extent to which the computer-generated counts are reliable. Within Melo-D we would create a musical interpretation of an existing database of fish detections to allow the biologist, for example, to explore the results of a specific query, and adjusting parameters to optimise the query result. Alternatively, the normally “silent” process of capturing and analysing new video material could be “melodised” so that biologists could immediately hear from the data that something unusual is happening.

At the start of the project we will ascertain the requirements related to specific tasks and data sets from the domain-specific scenarios to explore how users can develop a sonic approach to their work. We will identify meaningful musical traits for each specific data set and associated tasks. These may include, but are not limited to: harmony, timbre, tempo, structure and style, as well as temporal and tonal aspects.

We will carry out multiple iterations of exploring tasks that can usefully be supported with melodisation. The results will be distilled into a continually improving model of the requirements of a suitable dataset, characteristics of the task and potential melodisation combinations. The data abstractions explored will include low-level properties found in the data as well as high-level user-recognised domain properties. As we gain experience, we will develop a set of guidelines to be used in conjunction with the models.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Fluid dynamics | Urban soundscapes | Fish populations |
| Step 1a  Select dataset and determine appropriate data abstractions for 1 or 2 tasks | Digital particle Image velocimetry (DPIV) data recoding illuminated particles in the flow with a high-speed camera. Data pre-preprocessing to create vector field from flow topology | Current and past pedestrian flows provide a basis for selecting popular or quiet paths through a city. Relatively large numbers of photographs (e.g. flickr, Foursquare) indicate landmarks that can be found. | Determine relative abundances of fish for different species. Explore changes in fish abundance of several species during a year; monitor incoming video data. |
| Step 1b  Determine combination of musical traits | Meaningful musical traits will be developed in conjunction with users. We will create melodic themes and variations associating, for example:   * turbulence intensity, flow speed and periodicity to tempo, key and contour, allowing consonance roughness to indicate emerging turbulence; * landmark locations and pedestrian flow to individual leitmotifs and thematic pitch progression, allowing crowds to accentuate and build the swell of a particular location; * abundance of different species to clarity and brightness of chords and certainty scores of species identification to scales with unequal steps, allowing users to identify relative changes in species abundance. | | |
| Step 1c  Implement test environment | Melodic representations will be created using tools such as Supercollider. This supports OSC (Open Sound Control), allowing the data analysis to be implemented in other languages and the results mapped into sound. Initially the mapping will be only from data values to music rendition, but after a satisfactory rendition has been determined, tools will be supplied to allow the user to explore the wider melodic space. | | |
| Step 1d  Carry out user evaluations | We will use standard qualitative and quantitative human computer interaction methods. We will start with qualitative investigations to obtain feedback from users using *directed tasks with relatively simple melodisations on a pre-selected portion of the data*. As we gain knowledge about the users’ understanding of the interpretations of the data we will continue in two directions: *improve the melodisations* (necessary for users to be able to use the system more effectively) and, more importantly, understand to what extent *users are able to understand and develop some degree of confidence in the interpretations* that the melodies are able to convey. During task execution we will measure perceived mental effort, an index of cognitive load that allows the comparison of conditions by combining mental effort ratings with performance scores. Results can be compared with task execution using existing visual interfaces. As our melodisations improve and users become accustomed to them, we will use quantitative studies to understand better which melodisations are more appropriate for which task & data characteristics. The creation of melodic interfaces to the data analyses is a non-trivial task, requiring expert involvement. This complexity leads us to anticipate that users of the system will require time to fully understand it, and more time to be able to use it for tasks not pre-specified by ourselves. If the system proves to be sufficiently robust within the lifetime of the project, then we will also carry out longer-term studies to understand how their usage and understanding of the system develops with extended use. | | |
| Step 2  Analyse results of application domains | Combinations of melodic traits used for successful renditions for the different domains will be related to the properties of the data sets and tasks. These insights will be used to determine suitable tasks, data sets and melodic trait combinations for a subsequent iteration of Step 1 for the different domains. | | |
| Iterate Steps 1 and 2 | | | |
| Step 3  Collate results from all tasks and evaluations | Construct models of:   * tasks that can usefully be carried out with melodisations; * data properties that can be usefully transformed to melodic renditions; * combinations of melodic traits that allow users to extract useful domain information.   Provide guidelines for applying the above models in new domains. | | |

**Table 1: Outline of research processes**

The *tasks* most pertinent to Melo-D are those that require the interpretation of large quantities of data, namely exploratory inspection and trend identification.

*Data* characteristics can be continuous variables, such as speed or distance, or discrete, such as fish species or landmarks. Numbers of pedestrians or fish may change from being discrete, for small numbers, to continuous, for larger numbers. The melodic rendition should be able to take this into account. Specific objects, e.g. landmark of fish species, or states, e.g. a steady flow of pedestrians, might have their own leitmotifs that could be varied depending on other data values in the system. In order to create specific mappings, we need first to understand what users perceive as “normal” and “abnormal”, or identify distinct states within the system that may exist in combination with each other.

The essence of Melo-D is how combinations of variables in the data can be rendered through *combinations of musical traits*. We will use single variables mapped to single traits as a baseline. For example, a continuous domain variable, such as speed, may be translated into a continuously varying musical trait, such as pitch. An example of a more complex mapping would be to create melodic themes and variations using chords and multiple voices to associate abundance of different species that can be heard at the same time. The perception of musical chords composed of multiple complex tones is often perceived as aggregate acoustic properties rather than individual notes. This allows a state of a dataset to be conveyed as an aggregate and that aggregate to split out to multiple voices in reaction to some pre-specified change.

Ideally *users* should be able to choose the type of music they would like to hear generated in the system. We will investigate this at a later stage of the project.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | P1 | P2 | P3 | P4 | *Total per task* |
| Step 1a: Select dataset and determine appropriate data abstractions for 1 or 2 tasks | 12 | 12 | 3 | 12 | *39* |
| Step 1b: Determine combination of musical traits | 7 | 7 | 12 | 7 | *33* |
| Step 1c: Implement test environment | 18 | 18 | 12 | 24 | *72* |
| Step 1d: Carry out user evaluations | 18 | 18 | 6 | 12 | *54* |
| Step 2: Analyse results of application domains | 12 | 12 | 3 | 12 | *39* |
| Iterations of Steps 1 and 2 included in PMs above |  | | | | |
| Step 3: Collate results from all tasks and evaluations | 12 | 12 | 0 | 12 | *36* |
| *Total per partner* | *79* | *79* | *36* | *79* | **273** |

**Table 2: RTD Person Months per Partner and per Task**

We will consider ourselves successful when users are able to:

* demonstrate understanding of some aspect of a dataset through a melodic rendition;
* replicate a task that they currently do in some other way.

We will consider ourselves very successful when users are able to:

* complete a useful task that was not previously possible with a visual representation.

