Adapting general purpose interfaces to synthesis engines using unsupervised dimensionality reduction techniques and inverse mapping from features to parameters

Stefano Fasciani
University of Wollongong, fasciani@uow.edu.au

Lonce Wyse
National University of Singapore

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The investment of play constitutes a music-centered interaction between a musician and DMI system. An investment of play yields:

- Conceptual transfer
- Performatory i.e. adroit, fluent action
- Refined musical expression
- Elements of personal style
- Reproducible interaction

The Bent Leather Band studies suggest that expression is proportional to the amount of investment of play. Practicing and performing in a duo may have the potential to double expressivity capable.

5. CONCLUSION

In this paper, we develop adaptive techniques for mapping generic user interfaces to synthesis engines. Upon selecting a subset of synthesis parameters, the system automatically finds the parameters-to-sound deterministic relationship in a multidimensional space. We analyze this sonic space using two different unsupervised dimensionality reduction techniques and build the mapping using statistical information on a lower, but maximally representative, number of dimensions. The result is an adaptation of any general-purpose interface to a specific synthesis engine, providing direct control over the perceptual features with greatest variance. This approach guarantees a linear relationship between control signals and perceptual features, and at the same time, reduces the control space dimensionality maintaining the maximum exploitability of the sonic space.

1. INTRODUCTION

Synthesis engines often expose a large set of parameters to users. Runtime variation of the parameters produces modification in the sound generated as well as in its perception. Users generally require to establish the “mapping” between control signals and system parameters. Since controllers and synthesis engines are not of the same controller with different synthesizers and perception. This approach guarantees a linear relationship between control signals and perceptual features, and at the same time, reduces the control space dimensionality maintaining the maximum exploitability of the sonic space.

2. RELATED WORK

Within the majority of control devices and synthesis engines the flexibility of the control signals to parameters is fairly basic: the range and occasionally the standard dependencies, correlations and nonlinearities. Users often need to provide the system with some kind of manual intervention to adapt the only available options. Therefore, even assuming that it is possible to garner a heuristic understanding of the parameters-to-sound relationship, the desired mapping implementation might be impossible without the introduction of an intermediate processing layer.

In this work, we propose a technique to adapt a general-purpose interface to synthesis engine through:

- automatic analysis of the synthesis engine parameter-to-sound relationship based on perceptually related audio features;
- generation of an adaptive mapping based on the application of unsupervised dimensionality reduction techniques on the multidimensional perceptual sonic space.

Similar one-to-one, one-to-many or many-to-many mappings have been developed through the introduction of an intermediate layer in the perceptual space. Our work is focused on reducing the burden on the user who needs only to provide the system with information about the variable synthesis parameters. The dimensionality of the control space (number of independent signals from the control interface) can be set or modified a posteriori. Other than enabling direct control over perceptual aspects of the synthesized sound, which are user-defined, this technique introduces two additional benefits:

- a linear relationship is created between the control signal and the variation in the generated sound, avoiding situations where the controllers’ range leads to drastic sound variation or to null sound variation;
- an optimal mapping is created from a control signal space C, with dimensionality c, to
The optimal mapping is defined as the one allowing the best synthesis of sounds when projecting the control space C into the perceptual features in the sonic spaces D, directly related to the synthesizer parameter space P. The number of concurrent signals contributed through human cognitive and physical limitations. The consequence is that the dimensionality of C is generally much smaller than P. Figure 2 in a generic control interface driving a synthesis engine through the perceptual sonic space. In our approach this space is retrieved automatically and analysed with unsupervised dimensionality reduction techniques in order to compute the adapted mapping between control interface and synthesized sound.

**2. SYNTHESIS ENGINE PARAMETERS-TO-SOUND ANALYSIS**

Within this context we define a synthesis engine as any chain of algorithmic processes that produce audio. We consider this chain of processes as a black box that converts vectors p of synthesis parameters into sound. Moreover we assume a deterministc behaviour, excluding the presence of any stochastic component within the chain. Hence it is possible to state that given a vector p there is one and only one associated sound generated by the synthesis engine. The opposite of this statement may not be always true, since depending on the synthesis engine, different control p may lead to identical or very similar sounds. This will be taken into consideration in the adaptive mapping strategy in Section 3 to avoid potential noisy or discontinuous output.

The set of unique combinations of synthesis parameters p, is defined upon selecting the variable parameters, their respective maximum value, minimum value and sampling resolution. Here we assume that each parameter is in the range [0,1] (if not a simple scaling operation is applied). Choosing j parameters, the cardinality of p is given by the equations below.

\[ |p| = \prod_{i=1}^{j} |p_i| \]  

\[ p_i = \text{max}(p_i) - \text{min}(p_i) \]  

\[ p_i = \frac{p_i - \text{mean}(|p_i|)}{\text{std}(|p_i|)} \]  

Equation (1) shows the cardinality of p, computed through the product of the cardinality of each p, which in turn depends on the individual maximum, minimum, and sampling resolution (2). The set p can be represented with a matrix P, where each column is a vector p (unique combination of synthesis parameters).

The cardinality of p, and the size of P grow exponentially with the number of parameters j, and linearly with the sampling resolution values. The selection of these values is a trade-off between the level of detail in the synthesis engine analysis and the size of P. The size of this matrix affects not only memory but computational load as well, as discussed in Section 3.

The sound is generated for each p and analyzed to produce a corresponding vector d, using a fixed note on the chromatic scale. For each unique combination of synthesis parameters we compute not one but a sequence of vectors containing perceptually related features. For timbre that is static over time, the d sequence corresponding to the fixed p is set to the mean of the sequence of computed feature vectors. This helps to minimize the presence of low frequency oscillations (LFOs) in the synthesized sound. The sequence of feature vectors is used also to capture extra information about the dynamic aspect of the sound. The vector d corresponding to the fixed p is set to the mean of the sequence of vectors, adding an extra scalar, which represents the timbre periodicity. Autocorrelation is used to compute the periodicity of each computed feature. If different periods are detected, their mean is used instead. The size and number of the analysis windows defines the minimum detectable periodicity, while window overlap affects the maximum. For a better characterization of the dynamic aspect, the vector d can be further extended adding a periodicity value and oscillation range for each perceptually related feature, tripling its size.

Vectors d are stored in a matrix D and together with P fully characterize the parameters-to-sound relationship of the synthesis engine in the perceptual sonic space. Through column indexing it is possible to associate the p unique combinations of synthesis parameters with the relative perceptual features vector d. The adaptive mapping is based on the information embedded in these two matrices.

**3. ADAPTIVE MAPPING**

Here we assume that the general-purpose control interface generates a set of independent signal segments, each related to a unique combination of synthesis parameters over the range [0,1] and with uniform distribution. Therefore the space C, with dimensionality c, can be approximated with a hypercube. To obtain an adaptive mapping we further analyze the matrix D to generate another hypercube in a projected perceptually related parameter space, then the mapping is simply obtained by linking the two hypercubes. The number of control signals does not affect the result of the two post-processing stages to define the mapping; its posterior definition simply restricts the navigable sonic space to a certain number of dimensions. However this method guarantees that even with a limited control space dimensionality c, the perceptual feature space is explored along the directions corresponding to the maximum variability. This method may not always correspond to the maximum variability in the pure human perception. We describe and apply two different unsupervised selection of these dimensionality reduction techniques: PCA (Principal Component Approach) and ISOMAP, both followed by a statistical analysis from which the mapping is derived.

**3.1. Principal Component Approach**

PCA is an unsupervised technique that uses an orthogonal transformation to convert a set of multivariate observations of potentially correlated variables into a set of uncorrelated variables called Principal Components (PCs). Since the matrix D can have high dimensionality, we apply a stage of PCA to project the data into a lower dimensional space. The multivariate data in D is subjected to a prior whitening which scales each dimension to zero mean and unitary variance. The orthogonal and uncorrelated set of PCs is ranked by variance, representing the quantity of information carried by each. Mapping the hypercube C onto the PCs of Dc, guarantees control within the subspace where the perceptual features change the most. Compared to other works, the number of perceptually related features can be relatively high here. It is not necessary to have prior knowledge about features with synthesis engine parameter alteration. Perceptually meaningful features that are constant are automatically discarded. However, the user can compose and weight individual features in order to customize the adaptive result if desired. In this way it is possible to obtain a control focused on specific perceptual features that are not necessarily the dominant in terms of absolute variability.

To provide a response that is as linear as possible, it is necessary to analyze the data across the PCs. For each dimension the density is estimated through a histogram in a number of bins proportional to the product of the inverse of the sampling resolutions. Since PC ranges with low density should be explored with a finer step compared to those with high density, a mapping complementary of the histogram, represented in (5) hitochrome. For each PC the mapping function is based on its normalized integral, implemented through the cumulative sum in the discrete domain. Two examples of c (vertical axis) mapping over the PC (horizontal axis) are showed in Figure 2, where the black continuous line represents the mapping function. Equation (4) shows how the control signal c is transformed into a PC value through the inverse of the mapping function m, (5).

**Figure 1.** Synthesis engine control through the perceptually related sonic space.

**Figure 2.** An example of histograms (scaled 10x) and mapping functions m, (solid line) for the first two PCc.
synthesis engine control parameters space \( P \), with dimensionality \( p \), with \( c < p \).

The optimal mapping is defined as the one allowing the highest degree of success when projecting the control space \( C \) into the perceptual features in the sonic spaces \( D \), directly related to the synthesizer parameter space \( P \). The number of concurrent signals controlled through human interface is constrained by human cognitive and physical limitations. The consequence is that of dimensionality \( c \) is generally much smaller than \( P \). Figure 1 presents a generic control interface driving a synthesis engine through the perceptual sonic space. In our approach this space is retrieved automatically and analyzed with unsupervised dimensionality reduction techniques in order to compute the adapted mapping between control interface and synthesized sound.

### 2. SYNTHESIS ENGINE PARAMETERS-TO-SOUND ANALYSIS

Within this context we define a synthesis engine as any chain of algorithmic processes that produce audio. We consider this chain of processes as a black box that converts vectors of synthesis parameters into sound. Moreover we assume a deterministic behaviour, excluding the presence of any stochastic component within the chain. Hence it is possible to state that given a vector \( p \), there is one and only one associated sound generated by the synthesis engine. The opposite of this statement may not be always true, depending on the synthesis engine, different control \( p \) may lead to identical or very similar sounds. This will be taken into consideration in the adaptive mapping strategy in Section 3 to avoid potential noisy or discontinuous output.

The set of unique combinations of synthesis parameters \( p_{se} \) is defined upon selecting a subset of the variable parameters, their respective maximum value, minimum value and sampling resolution. Here we assume that each parameter is in the range \([0,1]\) (4) that the simple scaling operation is applied. Choosing \( j \) parameters \( p_j \) the cardinality of \( p_{se} \) is given by the equations below:

\[
\begin{align*}
|p_{se}| &= \prod_{i=1}^{j} |p_i| \\
|p_i| &= \max(p_i) - \min(p_i) \quad \text{(1)} \\
|p_{se}| &= \prod_{i=1}^{j} |p_i| \\
P_{se} &= p_{min} - p_{max} \quad \text{(2)} \\

\text{Equation (1) shows the cardinality of } p_{se} \text{ computed through the product of the cardinality of each } p_j \text{ which in turn depends on the individual maximum, minimum, and sampling resolution (2). The set } p_{se} \text{ can be represented with a matrix } P, \text{ where each column is a vector } p \text{ (unique combination of synthesis parameters).}

The cardinality of \( p_{se} \) and the size of \( P \) grow exponentially with the number of parameters \( j \) and linearly with the sampling resolution values. The selection of these values is a trade-off between the level of detail in the synthesis engine analysis and the size of \( P \). The size of this matrix affects not only memory but computational load as well, as discussed in Section 3.

### 3.1. Principal Component Approach

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Compared to other works, the number of perceptually related features can be relatively high here. It is not necessary to have prior knowledge about variations of features with synthesis engine parameter alteration. Perceptually meaningful features that are constant are automatically discarded. However, the user can compose and weight individual features in order to customize the adaptive mapping to their needs. In this way it is possible to obtain a control focused on specific perceptual features that are not necessarily the dominants in terms of absolute variability.

To provide a response that is as linear as possible, it is necessary to analyze the data across the PCs. For each dimension the density is estimated through a histogram with a number of bins proportional to the product of the inverse of the sampling resolutions. Since PC ranges with low density should be explored with a finer step compared to those with high density, we select the complement of the histogram, represented in (5) \( \delta_{p_{se}} \).

For each PC the mapping function is based on its normalized integral, implemented through the cumulative sum in the discrete domain. Two examples of \( c \) (vertical axis) mapping over the PCi (horizontal axis) are shown in Figure 2, where the black continuous line represents the mapping function. Equation (4) shows how the control signal \( c \) is transformed into a \( P_{se} \) value through the inverse of the mapping function \( m \).

\[
PC_j = m^{-1}(c_j) \quad \text{(4)}
\]

\[
m(c) = \int \delta_{p_{se}}(p_j) dp_j \quad \text{(5)}
\]

### Figure 1: Synthesis engine control through the perceptually related sonic space.

### Figure 2: An example of histograms (scaled 10x) and mapping functions \( m \) (solid line) for the first two PCi.
The interface signals c are used to generate a value of the first c PC of Dc with linear interpolation, obtaining a d, in the principal components space. The number of components considered in the system is limited to the number carrying 90% of the total energy. If c is smaller than the number of PC, the control signal mapped on the lower rank component is optionally mapped at the same time also on all the remaining ones.

3.2. ISOMAP Approach

ISOMAP is a low-dimensional embedding method [8], where geodesic distances on a weighted graph are incorporated with classical scaling. It is exploited to compute a quasi-isometric, low-dimensional embedding of a set of high dimensional data points. At the same time this algorithm provides a simple method for estimating the intrinsic geometry of a data manifold.

The main difference with other multi dimensional scaling methods is in the choice of the geodesic distance metric, rather than the Euclidean one. In ISOMAP, the geodesic distance is the sum of edge weights along the shortest path between two nodes, computed using Dijkstra’s algorithm. The top n eigenvectors of the geodesic distance matrix represent the coordinates in the new n-dimensional Euclidean space ISOMAP implements a transformation of the space, while PCA projects the data into a new coordinates system in the same space.

Dimensionality reduction with ISOMAP is applied to D with the same method described in the previous subsection for PCA. The mapping of the c control signals on the new coordinates system, named ISO, is based on an estimation of densities and distributions as before. ISOMAP has a higher computational cost compared to PCA, but it detects and exploits the embedded manifold, achieving a more effective dimensionality reduction. ISOMAP is preferred when the control space C has a very low dimensionality. This difference is evident when comparing the energy in each dimension of the residual variance. Figure 3 shows an example of an energy distribution, measured in terms of variance, across the PC and ISO for the same data set.

The number of vectors D in Dc can be lower than Dc because the ISOMAP algorithm includes an outlier removal stage. To guarantee coherence, the number of elements in Dc and P must be the same. Hence the vectors p relative to the outliers are removed from P.

3.3. Synthesis engine parameters retrieval

For both approaches, after the generation of the vector Dc (or Dd) we search the nearest neighbour vector in the matrix Dc (or Dd). Through column indexing we retrieve from P the vector p used to drive the synthesis engine instantaneously. This simple approach leads to potential discontinuity in the synthesis parameters generation, because different combinations of synthesis parameters that might be far apart in the control space may lead to identical or near points in the perceptually related feature space. To guarantee continuity we propose two solutions. In the first one we retrieve K NN (nearest neighbours) in Dc rather than one and drive the synthesis engine with the mean of the K corresponding vectors p. In the second one, before searching for the nearest neighbour, we append p to the Dc (or Dd), and we append the matrix P to Dc (or Dd). The first solution shows a limitation when the K p are very far apart, while the second can be debatable because perceptual features and synthesis parameters are merged in the same functional space, hence the search is performed in a heterogeneous space. However, these methods improve a shortcoming in [5] where occasionally the system gets trapped in local minima.

As mentioned before, the sampling resolutions affect the size of P and D. The computational load required for the K NN search is thus proportional to the size of the matrix and it affects the system minimum response time.

4. PROTOTYPE AND APPLICATION

A prototype has been developed and is implemented in Max/MSP and MATLAB. The prototype uses the FTM [9] and MaxM [10] toolbox for vector and matrix processing in Max/MSP. The perceptually related feature set is based on Tristan Jehan’s “analyzer~” by Miller Puckette max external. The feature vector hence includes: loudness, pitch, brightness, noiseiness, and the energies in the 25 Bark bands. Each feature can be enabled/disabled by the user and a weight vector can be defined as well to provide better customization. The adaptive approach is independent of the dimensionality and content of the feature vector, therefore a different selection is possible. The prototype is integrated with Ableton Live using the Max For Live framework for the interfacing capabilities with state-of-the-art synthesis engines. Two Max For Live patches cooperate to analyze the synthesis engine. The front-end generates the p set and drive the synthesizer with up to 8 parameters, and the back-end analyses the audio signal, stores the p, and the relative multiple d, in the matrices P and D. The post processing of D described in Section 2, and the adaptive mapping described in Section 3, are computed within MATLAB using the author’s ISOMAP implementation. Another two Max For Live patches implement the runtime adaptive control for PCA and ISOMAP respectively, exposing up to 4 PC/ISO mapped control parameters.

Through the prototype’s Max For Live patches it is possible to set and modify several system settings allowing exploration of different configurations. In the analysis patches it is possible to set the sampling resolutions, the parameters range, the note and the timing (in terms of delays) of the automatic analysis. Moreover, the number of analysis windows and the hop size are flexible, while the window size is fixed at 4096 samples. The control patches allow further reduction of the dimensionality of the PCA projection and ISOMAP transformation, modification of the K NN number, and the dimensionality of the control space C. The prototype allows also for inverting the polarity of every PC or ISO, in order to flip the synthesis engine response.

4.1. Single Parameter Application

In this first application we chose a simple scenario to demonstrate the adaptation capability. The synthesis engine is the Ableton Live Operator synth, implementing a simple FM synthesis using just two oscillators. The only variable parameter is the cut-off frequency of the low pass filter. We run the analysis over the full range of the parameter and a reduced set of features, using the energy of Bark bands only. Four analysis windows per state p are computed with a hop size of 2048 samples, using C2 as fixed note. For the mapping we use only the principal dimension from the PCA and ISOMAP methods in order to have a 1D compression metric. Both provide an identical result in terms of adapted control: most of the energy is concentrated on the first parameter since there is high correlation in D. Figure 4 shows three-dimensional scatter plot of the first three PC, or ISO (note the different axis ranges), where is possible to appreciate the capability of ISOMAP to detect the manifold and organize data. Figure 5 shows a line graph, how the adapted control provides a linear response over the feature with the greatest variance, while the control signal applied directly to the cut-off frequency presents a non-linear response and a range with almost no effect over the generated sound.

4.2. Two Parameters Application

In a second example, we run the analysis computing the complete features set on a preset of the Ableton Live Analog synth, modifying the two “oscillator detune” parameters with a coarse sampling resolution. Ten analysis windows per state p are computed with a hop size of 1024 samples, using C3 as fixed note. Figure 6 shows how the two principal PCA and ISOMAP projected perceptual features are very noisy over the control parameter space, but in Figure 7 it is evident that these are linear and stable due to the adaptive control. The wider range obtained with the ISOMAP is due to its capacity to embed energy in a lower number of dimensions.

Images of the Max For Live prototype patches are available at http://wwwlab.dsi.unive.it/ and http://isomap.stanford.edu/
The interface signals $c_i$ are used to generate a value of the first $c$ PC of $D_{PC}$ with linear interpolation, obtaining a $d_i$ in the principal components space. The number of components considered in the system is limited to the number carrying 90% of the total energy. If $c_i$ is smaller than the number of $PC$, the control signal mapped on the lower rank component is optionally mapped at the same index also on all the remaining ones.

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1 Images of the Max For Live prototype patches are available at http://sunlab.org/downloads/maxscan_images.zip

2 http://isomap.stanford.edu/
4.3. Partikkel Hadron Application

In the last example we use the Partikkel Hadron1 granular synthesizer with one of the provided pre-set. Through granular synthesis it is possible to obtain large timbre variation due to the nature of the synthesis, but often the control parameter set is large and challenging to design an interface for. This device exposes just 6 parameters for timbre manipulation thanks to the exploration of the Modulation Matrix [7]. We analyze the generated audio with 25 Bark bands energies over the whole control space given by all possible combinations of the 6 parameters. Sixteen analysis windows per state \( p \) are computed with a hope size of 512 samples, using C2 as fixed note. In this more complex scenario the performance of ISOMAP is sensibly better than PCA. The data presented in Figure 8 shows how ISOMAP, when compared with PCA, allows the reduction of at least one dimension in the control space \( C \) without losses in the overall descriptors space energy. With the ISOMAP adaptation, we obtain a further reduction of the control space. This enables the use of a simple 2D controller, while still permitting the navigation of the majority of the granular sonic space spanned by the original 6 parameters.

![Figure 8: A MICROPHONE ARRAY INTERFACE FOR REAL-TIME INTERACTIVE MUSIC PERFORMANCE](image)

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1. INTRODUCTION

Recently, microphone array signal processing is increasingly being used in human computer interaction systems, for example the new popular interface Microsoft Kinect incorporates a microphone array to improve the voice recognition using the acoustic source localization and the beam-forming for noise suppression. In the past years, a large number of musical interfaces has been implemented with the goal of providing tools for gestural interaction with digital sounds, using systems played by touching or holding the instrument, interfaces with haptic feedback, systems worn on the body, and interfaces that may be played without any physical contact (electric field sensors [12], optical sensors [7], ultrasound systems [10], and video camera that allows the performer to use their full-body for controlling in real-time the generation of an expressive audio-visual feedback [1]).

A novel digital musical interface based on sound source localization using a microphone array is presented. It allows a performer to plan and conduct the expressivity of a performance by controlling an audio processing module in real-time through the spatial movement of a sound source. Musical interfaces are often used to allow the control to enhance the expressive control on the sounds generated by their acoustic instruments in a live electronics context. E.g., in the works by Adriano Guarnieri – Medico (2002) and Filippo Bianco – Velati (2005) - produced at the “Centro di Sonologia Computazionale” of Padova, the movement of a musician is followed by a motion capture system based on infrared cameras to control a live electronics patch [4], and using the robot for very expensive, PhaseSpace optical motion capture system. It is composed by led systems, video cameras, and calibration procedure. In general, those kind of systems have considerable complexity and in some situations there could be problems with the low and/or not always controllable lighting of the concert hall, even when using infrared camera. It has been shown in [14] that there is some potentiality in using the sound source localization to directly control the position of a sound played back through a spatialization system by moving the sound produced by its own musical instrument. This work has been improved in [13] introducing an adaptive parameterized Generalized Cross-Correlation (GCC) PHAT filter to localize musical sounds that are mainly harmonics. Both interfaces [14] [15] are been tested in a controlled real environment verifying how the system works with interfering sources from a sound reinforcement system and other instruments. Thus, in this paper a validation in multi-source scenario is presented, introducing the adaptive parameterized SRP-PHAT with a ZCR threshold (Section 3) that has a better performance than the parameterized GCC-PHAT proposed in [13] as shown in Section 4.