STEERING GENERATIVE RULES WITH THE EEG: AN APPROACH TO BRAIN-COMPUTER MUSIC INTERFACING

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ABSTRACT

This paper introduces a system that uses brainwaves, or EEG (electroencephalogram), information to steer generative rules in order to compose and perform music on the fly. The paper starts by noting the various attempts at the design of systems to produce music from EEG, followed by a short technical introduction to EEG sensing and analysis. Next, it introduces the generative component of the system, which employs Artificial Intelligence techniques (e.g., ATN grammars) for computer-replication of musical styles. Then, it presents a demonstration system that constantly monitors the EEG of the subject and activates generative rules that are associated with the most prominent frequency band in the spectrum of the EEG signal. The system also measures the complexity of the EEG signal in order to modulate the tempo (beat) and dynamics (loudness) of the performance. The paper concludes with a brief discussion on the achievements and limitations of our research so far, and comments on its contribution for the development of assistive technology for severe physical and neurological disability, which is one of the main goals of this work.

1. INTRODUCTION

Human brainwaves were first measured in 1924 by Hans Berger [5]. Today, the EEG has become one of the most useful tools in the diagnosis of epilepsy and other neurological disorders. Further, the fact that a machine can read signals from the brain has sparked the imaginations of scientists, artists and other enthusiasts, and the EEG has made its way into a myriad of other applications.

In the early 1970s, Jacques Vidal did the first tentative work towards a system to communicate with a computer with the EEG. The results of this work were published in 1973 in a paper entitled *Toward Direct Brain-Computer Communication* [30]. This field of research is known as Brain-Computer Interface (BCI) and there is a growing number of researchers worldwide working in this field. Many attempts followed with various degrees of success. To cite but one example, in 1990, Jonathan Wolpaw and colleagues developed a system to allow primitive control of a computer cursor by subjects with severe motor deficits. Subjects were trained to use their EEG to move the cursor in simple ways [31]. For recent reports on BCI research please refer to the special issue of *IEEE Transactions on Biomedical Engineering* published in June 2004 (Vol. 51).

We are devoted to the development of BCI systems for musical applications and we pay special attention to the development of generative music techniques tailored for such systems. We might call such systems Brain-Computer Musical Interfaces (BCMI) and we are primarily interested in BCMI as assistive technology to enable people with severe physical and neurological disabilities to have the opportunity to make music.

The idea of using EEG to produce music is by no means new. Essentially, what is new in our work is the use of EEG information to steer generative rules.

As early as 1934, a paper in the journal *Brain* had reported a method to listen to the EEG [1]. It is now generally accepted that it was composer Alvin Lucier, who composed the first musical piece using EEG in 1965: *Music for Solo Performer* [16]. Pioneers such as Richard Teitelbaum [28], David Rosenboom [26, 27] and a few others followed with a number of interesting systems and pieces. Back in 1975 David Rosenboom edited a remarkable book on the topic [25] and more recently Andrew Brouse published a review on using brainwaves to produce music [8].

Our research builds on the work developed by these pioneers in a number of ways. Firstly, we are employing and developing more sophisticated analysis techniques to harness the EEG signal. Furthermore, we are developing new psychophysical experiments in order to gain a better understanding of the EEG components associated with musical cognition and methods to train subjects to generate such EEG components. Finally, we are developing generative techniques especially designed for musical composition and performance with a BCMI. The psychophysical experiments are beyond the scope of this paper. More details about this aspect of the research can be found in [18, 19].

2. TECHNICAL BACKGROUND

The EEG is measured as the voltage difference between two or more electrodes on the surface of the scalp (Figure 1), one of which is taken as a reference.

The EEG expresses the overall activity of millions of neurons in the brain in terms of charge movement, but the electrodes can detect this only in the most superficial regions of the cerebral cortex.

There are basically two conventions for positioning the electrodes on the scalp: the *10-20 Electrode Placement System* (as recommended by the International Federation of Societies for EEG and Clinical Neurophysiology), and the *Geodesic Sensor Net* (developed by a firm called Electric Geodesics, Inc.). The former is more popular and is the convention adopted for the systems described in this paper: it uses electrodes placed at positions that are measured at 10% and 20% of the head circumference (Figure 2). In this case, the terminology for referring to the position of the electrodes uses a key letter that indicates a region on the scalp and a number: F = frontal, Fp = frontopolar, C = central, T = temporal, P = parietal, O = occipital and A = auricular (the ear lobe; not shown in Figure 2). Odd numbers are for electrodes on the left side of the head and even numbers are for those on the right side.

The set of electrodes being recorded at one time is called a *montage*. Montages fall into one of two categories: *referential* or *bipolar*. Referential means that the reference for each electrode is in common with other electrodes; for example, each electrode may be referenced to an electrode placed on the earlobe. An average reference means that each electrode is compared to the average potential of every electrode. Bipolar means that each channel is composed of two neighbouring electrodes; for example, channel 1 could be composed of Fp1-F3, where Fp1 is the active electrode and F3 is the reference, then channel 2 could be composed of Fp2-F4, where Fp2 is the active electrode and C4 is the reference; and so forth.

Figure 1. Brainwaves can be detected with electrodes placed on the scalp.

The EEG is a difficult signal to handle because it is filtered by the meninges (the membranes that separate the cortex from the skull), the skull and the scalp before it reaches the electrodes. Furthermore, the signals arriving at the electrodes are sums of signals arising from many possible sources, including artifacts like the heartbeat and eye blinks. Although experts can diagnose brain malfunctioning from raw EEG plots, this signal needs to be further scrutinized with signal processing and analysis techniques in order to be of any use for a BCI system.

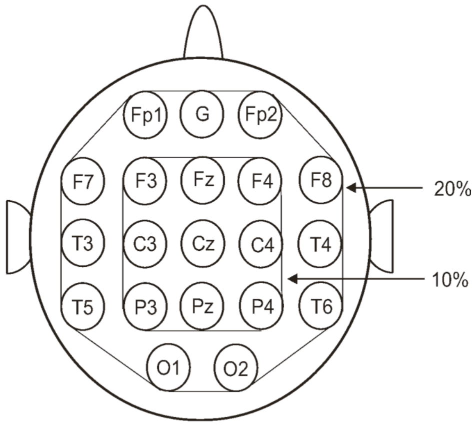

Figure 2. The 10-20 electrode placement system.

2.1. EEG Analysis

There are a number of approaches to EEG analysis, such as *power spectrum*, *spectral centroid*, *Hjorth, event-related potential (ERP)*, *principal component analysis (PCI)*, *correlation*, to cite but a few. Brief non-mathematical introductions to EEG power spectrum and Hjorth analyses are given below due to their relevance to our system. A discussion on other analysis techniques and how they have been used in neuroscience of music research can be found in references such as [6, 13, 14, 21, 29].

Power spectrum analysis is derived from techniques of Fourier analysis, such as the Discrete Fourier Transform (DFT). In short, DFT analysis breaks the EEG signal into different frequency bands and reveals the distribution of power between them. This is useful because the distribution of power in the spectrum of the EEG can reflect certain states of mind. For example, a spectrum with salient low-frequency components can be associated with a state of drowsiness, whereas a spectrum with salient high-frequency components could be associated with a state of alertness. There are five recognised frequency bands of EEG activity, also referred to as *EEG rhythms*, each of which is associated with specific mental states: *delta*, *theta*, *alpha*, *low beta* and *high beta* rhythms. They certainly indicate different mental states, but there is, however, some controversy as to the exact boundaries of these bands and the mental states with which they are associated.

Hjorth introduced an interesting method for clinical EEG analysis [12], which measures three attributes of the signal: its *activity*, *mobility* and *complexity*. Essentially, it is a time-based amplitude analysis. This method is interesting because it represents each time step (or window) using only these three attributes and this is done without conventional frequency domain description. The signal is measured for successive epochs (or windows) of one to several seconds. Two of the attributes are obtained from the first and second time derivatives of the amplitude fluctuations in the signal. The first derivative is the rate of change of the signal's amplitude. At peaks and troughs the first derivative is zero. At other points it will be positive or negative depending on whether the amplitude is increasing or decreasing with time. The steeper the slope of the wave, the greater will be the amplitude of the first derivative. The second derivative is determined by taking the first derivative of the first derivative of the signal. Peaks and troughs in the first derivative, which correspond to points of greatest slope in the original signal, result in zero amplitude in the second derivative, and so forth.

Activity is the variance of the amplitude fluctuations in the epoch. Mobility is calculated by taking the square root of the variance of the first derivative divided by the variance of the primary signal. Complexity is the ratio of the mobility of the first derivative of the signal to the mobility of the signal itself. A sinewave has a complexity equal to 1. Figure 3 shows an example of Hjorth analysis. A raw EEG signal is plotted at the top (C:1) and its respective Hjorth analysis is plotted below: activity (C:2), mobility (C:3) and complexity (C:4).

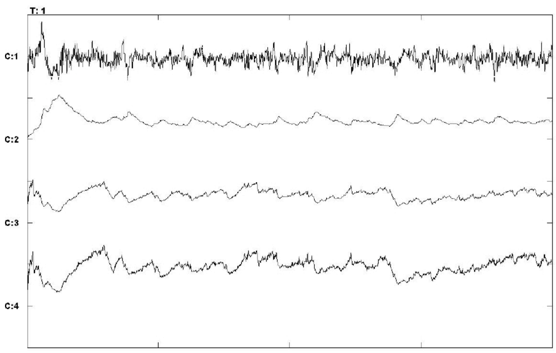

Figure 3. An example of Hjorth analysis.

There is no clear agreement as to what these measurements mean in terms of mental states. It is common sense to assume that the longer a subject remains focused on a specific mental task, the more stable is the signal, and therefore the lower is the variance of the amplitude fluctuation. However, this point questions the possible affects of fatigue, habituation and boredom, which we have not yet accounted for in our research.

2.2. Generative Rules

The system uses a rule system that generates music, based on given examples. The EEG-signals can influence in a well-defined way the mixture of different style-elements found in the different musical examples given to train the system. It can generate music that contains, for example, more Schumann-like elements when the spectrum of the subject's EEG contains salient low-frequency components and more modern or jazzy elements when the spectrum of the EEG contains salient high-frequency components. (These associations are arbitrary.)

Example-based musical-generation systems are often based on formalisms such as transition networks or Markov Chains to re-create the transition-logic of what-follows-what, either at the level of notes [15] or at the level of similar "vertical slices" of music [9, 10]. For example, David Cope uses such example-based musical-generation methods but adds phrase-structure rules, higher-level composition structure rules, and well-placed signatures, earmarks and unifications [9, 10]. The act of recombining the building blocks of music material together with some typical patterns and structural methods has proved to have great musical potential. This type of self-learning predictors of musical elements based on previous musical elements could be used on any level or for any type of musical element such as: musical note, chord, bar, phrase, section, and so on. However, there must be logical relations on all those levels; if a musical note is very close related to its predecessor(s) then a list of predecessors can predict quite well what note will follow. The same holds true for chords, phrase-level, and section-level elements.

For the moment, we have chosen to stick to a statistical predictor at the level of short vertical slices of music such as a bar or half-bar, where the predictive characteristics are determined by the chord (harmonic set of pitches, or pitch-class) and by the first melodic note following the melodic notes in those vertical slices of music (see example below).

We implemented a simple method for generating short musical phrases with a beginning and an end that also allows for real-time steering with EEG information. The system generates musical sequences by defining top-level structures of sentences and methods of generating similarity- or contrast-relationships between elements. Consider the following example (LISP-like notation):

```
S -> (INC BAR BAR BAR BAR BAR
      HALF-CADENCE 8BAR-COPY)
```

From this top-level, we then generate rules for selecting a valid musical building block for each symbol, including rules for incorporating the EEG information in all decisions. For example:

```
INC ->((EQUAL 'MEASURE 1)
       (EQUAL 'COMPOSER
              EEG-SET-COMPOSER))

BAR ->((CLOSE 'PITCH 'PREV-PITCH-LEADING)
       (CLOSE 'PITCH-CLASS
              'PREV-PITCH-CLASS-LEADING)
       (EQUAL 'COMPOSER
              EEG-SET-COMPOSER))
```

This defines a network that generates a valid sentence with a beginning and an end, including real-time EEG control through the variable EEG-SET-COMPOSER. The generative engine will find a musical element for each of the constraint-sets that are generated above from INC and BAR, by applying the list of constraints in left-to-right order to the set of all musical elements until there are no constraints left, or there is only one musical element left. This means that it can happen that some of the given constraints are not applied.

The database of all musical elements contains music from different composers, with elements tagged by their musical function such as *measure 1* for the start of a phrase, *cadence* for the end, *composer* for the composer, and the special tags *pitch* and *pitch-class* that are both used for correct melodic and harmonic progression or direction. The selection process is illustrated below.

The example database in the Appendix shows the main attributes that are used to recombine musical elements. P-CLASS (for *pitch-class*) is a list of two elements. The first is the list of start-notes, transposed to the range of 0-11. The second is the list of all notes in this element (also transposed to 0-11). P is the *pitch* of the first (and highest) melodic note in this element; by matching this with the melodic note that the previous element was leading up to we can generate a melodic flow that adheres in some way to the logic of "where the music wants to go". The PCL (for *pitch-class leading*) elements contain the same information about the original next bar; this is used to find a possible next bar in the recombination process. Then there are the INC, BAR, and CAD elements. These are used for establishing whether those elements can be used for phrase-starts (incipient), or cadence.

Simply by combining the musical elements with the constraint-based selection process that follows from the terminals of the phrase-structure rewrite-rules, we end up with a generative method that can take into account the EEG information. This generates musical phrases with a domino-game like building block connectivity:

```
((EQUAL 'MEASURE 1)
 (EQUAL 'COMPOSER EEG-SET-COMPOSER))
```

Assuming that there are also musical elements available from composers other than SCHU, the first constraint will limit the options to all *incipient* measures from all musical elements from all composers. The second constrains will then limit the options according to the current EEG analysis to the composer that is associated with the current EEG activity, as follows:

```
((CLOSE 'PITCH 'PREV-PITCH-LEADING)
 (CLOSE 'PITCH-CLASS
        'PREV-PITCH-CLASS-LEADING)
 (EQUAL 'COMPOSER EEG-SET-COMPOSER))
```

In the given phrase structure, the rule that follows from BAR then defines the constraints put upon a valid continuation of the music. These constrains will limit the available options one by one and will order them according to the defined rule preferences. The CLOSE constraint will order the available options according to their closeness to the stored value. For example, after choosing:

```
(SCHU-1-1-MEA-1
       P-CLASS ((0 4) (0 3 4 6 7 9))
       P 76
       PCL ((2 7 11)(2 5 7 9 11))
       PL 83
       BAR INC
       CO SCHU)
```

as the beginning, PREV-PITCH-LEADING will have stored 83, and PREV-PITCH-CLASS-LEADING will have stored ((2 7 11) (2 5 7 9 11)). This will result in measure 2 and 4 being ranked highest according to both pitch and pitch-class, and measure 6 and the cadence close according to pitch-class, while measure 6 is also quite close according to pitch. This weighted choice will give a degree of freedom in the decision that is needed to generate pieces with an element of surprise. The music will not get stuck in repetitive loops, but it will find the closest possible continuation when no perfect match is available. We can still find a close match in this way if the third constraint eliminates all the obvious choices that are available; e.g., because a jump is requested to the musical elements of another composer, who might not use the same pitch-classes and pitches.

We are currently exploring other possibilities with extra constraints and transformations on music that will generate music with repeated similarities (such as "unifications" [9, 10]), and larger structures such as the generation of rondos and variations, while still adhering in real-time to the demands of the EEG.

Figure 4 shows an example output with elements from the musical style of Robert Schumann and Ludwig van Beethoven. In this example the EEG jumped back and forth from bar to bar between the two styles. The harmonic and melodic distances are quite large from bar to bar, but still they are the optimal choices in the set of chosen elements from the two composers.

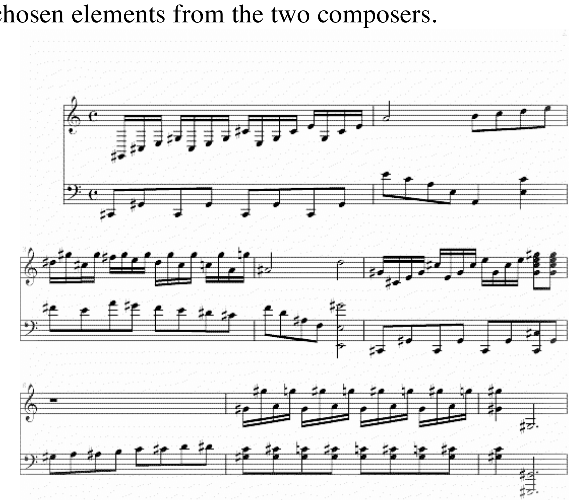

Figure 4. An example of a generated mixture of Robert Schumann and Ludwig van Beethoven.

3. THE DEMONSTRATION SYSTEM

The demonstration system falls into the category of BCI computer-oriented systems [18]. These systems rely on the capacity of the users to learn to control specific aspects of their EEG, affording them the ability to exert some control over events in their environments. Examples have been shown where subjects learn how to steer their EEG to select letters for writing words on the computer screen [7]. However, the motivation for this demonstration departed from a slightly different angle from other BCI systems. We aimed for a system that would make music by "guessing" the meaning of the EEG of the subject rather than a system for explicit control of music by the subject. Learning to steer the system by means of biofeedback would be possible, but we did not investigate this possibility systematically yet.

We acknowledge unreservedly that the notion of "guessing the meaning of the EEG" here is rather simplistic. Nevertheless we took the risk of suggesting this notion because it is a plausible notion: it is based on the assumption that neurophysiological information can be associated with specific mental activities [2, 24]. Continual progress in the field of Cognitive Neuroscience of Music is increasingly substantiating this assumption [23].

Figure 5. The demonstration system runs on two computers. The laptop performs the EEG analysis with Matlab/Simulink and the Macintosh generates the music with Max/MSP and Common Lisp. The units under the laptop are the EEG amplifiers.

The system is programmed to look for information in the EEG signal and match the findings with assigned generative musical processes corresponding to different musical styles. As mentioned in the previous section, these assignments are arbitrary. An example could be: if the system detects prominent alpha rhythms in the EEG, then it might activate assigned processes that generate musical passages in the style of Robert Schumann's piano works.

The EEG is sensed with seven pairs of gold EEG electrodes on the scalp, forming a bipolar montage. A discussion for the rationale of this configuration falls outside the scope of this paper. It suffices to say that we are not looking for signals emanating from specific cortical sites; rather, the idea is to sense the EEG over the whole surface of the cortex. The electrodes are plugged into a biosignal amplifier and a real-time acquisition system. The analysis module is programmed in Matlab/Simulink [17] to perform power spectrum and Hjorth analyses in real-time. The analysis module generates two streams of control parameters. One stream contains information about the most prominent frequency band in the signal and is used to generate the music. The other stream contains information about the complexity of the signal and is used to control the tempo (beat) and dynamics (loudness) of the performance. The generative music module is implemented in Max/MSP and Common Lisp. (A newer version of the system is being implemented in Miller Puckette's PD.)

The present demonstration activates generative rules for two different styles of music, depending on whether the EEG indicates salient low-frequency or high-frequency components (or EEG rhythms) in the spectrum of the EEG. Every time it has to produce a bar, it checks the power spectrum of the EEG at that moment and activates the generative rules accordingly.

Figure 6. The demonstration system in action using a Disklavier piano.

The system is initialised with a reference tempo (e.g., 120 beats per minute), which is constantly modulated by the signal complexity analysis (Hjorth analysis). The system sends out MIDI information for performance on a Disklavier piano, manufactured by Yamaha (Figures 5 and 6).

4. CONCLUDING DISCUSSION

The work presented in this paper is the result of intense multidisciplinary research, ranging from neuroscience and medical engineering to music technology and composition. Our research work owes an historical debt to the pioneering works of people such as David Rosenboom, Richard Teitelbaum and Alvin Lucier, but extends those works with new possibilities for much finer granularity of control over real-time musical processes.

Research into brain-computer music interfacing is an interesting arena for the development of new devices for performance and composition. However, with this research we are primarily interested in opening up new possibilities in recreational and therapeutic devices for people with physical and neurological disabilities.

There are various music-making devices available for those with disabilities, and even though these devices have proved to work very effectively, they often do not allow as much control for those with severe physical disabilities. At present, access music tutors use gesture devices and adapted accessible technology to make this possible, which achieve excellent results. For people with severe physical disabilities, however, having complete control of the environment created for them by the facilitator can sometimes prove difficult. For many with disabilities, EEG signals could be the only option of control and sometimes with others be a more reliable one, due to the nature of their disability.

At present, our system is being tested and assessed in professional recreational activities by a music facilitator. The results of these tests and assessments will be crucial to guide further developments. In the flowing paragraphs we briefly discuss some concluding issues that emerged during the research.

4.1. BCMI vs. Hard BCI Research

The BCI research community understands that a BCI system is a system that allows for the control of a machine by explicitly thinking the task(s) in question; e.g., control a robotic arm by thinking explicitly about moving an arm. This is a very difficult problem. The system presented in this paper does not address this type of explicit control. This would be even more difficult in the case of music.

However, we stress that we are not interested in a system that plays a melody by thinking the melody itself. Rather, we are furnishing our systems with Artificial Intelligence in order to allow them make their own interpretation of the meaning of the EEG patterns. Such machine-interpretations may not always be accurate or realistic, but this is exactly the type of man-machine interaction that we are addressing in our work.

4.2. Training

In order to have greater control over the system, we are developing methods to train subjects to achieve specific EEG patterns to control musical algorithms. We have initial evidence that this can be made possible using a technique known as *biofeedback*. Biofeedback is when biological information or signals are monitored electronically, which in turn feedback information about our body or physiological state. This information is often displayed through audio-visual stimuli. As a result the subject can learn to modify these signals and subsequently learn to gain greater control of the biological signals. Biofeedback technology is used to treat and control a number of conditions; examples include migraine headaches and epilepsy. In addition it has been used for artistic expression by composers such as David Rosenboom through music, performance and visual art [25, 26, 27].

4.3. Deciphering the EEG

Although powerful mathematical tools for analysing the EEG already exist, we still lack a good understanding of their analytical semantics in relation to musical cognition. However, continual progress in the field of cognitive neuroscience [23] is improving this scenario substantially. Once these issues are better understood we will be able to program our device to recognise patterns of cognitive activity in the brainwaves and activate appropriate musical algorithms associated with such patterns. Preliminary work in this regard has been reported in [18, 19].

4.4. Ergonomics

The non-ergonomic nature of the electrode technology for sensing the EEG is an aspect that needs to be addressed in future research. The current system is awkward to wear and uncomfortable. There are various possibilities for innovations in the hardware design of EEG capture devices. Inexpensive auto-scanning / auto-negotiating wireless chips are now available and could be placed on the head along with the small preamplifiers. It is thus possible to build wearable EEG amplifiers with built-in signal processing and wireless data transmission. The possibility of using other sensing and brain imaging technologies also needs to be addressed.

4.5. Quality of the Music

We acknowledge that the music produced by the system is of limited appeal for those interested in contemporary music. Furthermore, the pieces produced by our computer-replication of musical style system may not always sound convincing to discerning listeners. However, we decided to adopt the ATN-like approach developed by David Cope [7, 8] as a starting point for this research because ATN grammars are well understood and their use in music is well documented. Nevertheless, we are studying the possibility of using other interesting machine learning and generative techniques such as those proposed by Barbar et al. [4], Dubnov et al. [11], and Assayag and Dubnov (Factor Oracles) [3].

We did try our system with more adventurous and experimental compositional practices (cellular automata, stochastic schemes, etc.). However, we decided to stick to a more traditional pragmatic approach to musical composition, at least at this stage of the project. It proved to be less difficult to demonstrate the merits of our research to the scientific and medical community when the system produced music in styles that were more popularly known.

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6. APPENDIX

An excerpt from a database of musical elements where: **CO** = composer (SCHU = Robert Schumann.), **P-CLASS** = pitch class, **P** = pitch, **PCL** = pitch-class leading, **PL** = pitch leading and **TPE** = type.

```
ID        SCHU-1-1-CAD
CO        SCHU
P-CLASS   ((0 2 7)(0 2 4 5 7 11))
P         74
PCL       ((0 4 9)(0 2 4 5 7 9 11))
PL        76
TPE       CAD

ID        SCHU-1-1-MEA-6
CO        SCHU
P-CLASS   ((5 9)(0 5 7 9))
P         81
PCL       ((0 2 7)(0 2 4 5 7 11))
PL        74
TPE       BAR

ID        SCHU-1-1-MEA-5
CO        SCHU
P-CLASS   ((0 4)(0 4 7))
P         76
PCL       ((5 9)(0 5 7 9))
PL        81
TPE       BAR

ID        SCHU-1-1-MEA-4
CO        SCHU
P-CLASS   ((0 4)(0 3 4 6 7 9))
P         83
PCL       ((0 4)(0 4 7))
PL        76
TPE       BAR

ID        SCHU-1-1-MEA-3
CO        SCHU
P-CLASS   ((0 4)(0 3 4 6 7 9))
P         76
PCL       ((2 7 11)(2 5 7 9 11))
PL        83
TPE       BAR

ID        SCHU-1-1-MEA-2
CO        SCHU
P-CLASS   ((2 7 11)(2 5 7 9 11))
P         83
PCL       ((0 4)(0 3 4 6 7 9))
PL        76
TPE       BAR

ID        SCHU-1-1-MEA-1
CO        SCHU
P-CLASS   ((0 4)(0 3 4 6 7 9))
P         76
PCL       ((2 7 11)(2 5 7 9 11))
PL        83
TPE       INC
```