EVENT AND PROCESS IN THE FABRIC AND PERCEPTION OF ELECTROACOUSTIC MUSIC

A COMPARATIVE STUDY OF XENAKIS'S BOHOR AND METASTASEIS

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ABSTRACT

In previous work we have shown that acoustic intensity profiles can be strong predictors of continuous-response patterns of perceptions of change and affect expressed by classical and electroacoustic music. We studied a section of Trevor Wishart's *Red Bird* in depth, and began a study of Xenakis's *Bohor*. *Bohor* shares generic patterns of intensity change across the piece with many other electroacoustic (ea) pieces we have studied: crescendi are short, with a high rate of change of intensity, while decrescendi are longer and with slower rates of change. Here we used statistical techniques of time series analysis seeking to relate listener perceptions and acoustic properties of part of *Bohor,* and part of Xenakis's orchestral piece *Metastaseis*. Time series analysis models the ongoing *process* of the perceptual responses. We found that surface timbral features of the latter, such as tremelandi, brass entries, glissandi and silence, though related to acoustic intensity patterns, were separable influences on perception; they constitute perceptually important *events*. The basic acoustic features of the section of *Bohor* we studied are more homogeneous, and at least for listeners unfamiliar with the piece, perceptual responses correspondingly are slighter. Possible future developments in the study of perception of Xenakis's electroacoustic music, and ea music in general, are discussed.

1. INTRODUCTION

Our long-term project is to determine what structural features of chosen music are perceived by untrained listeners, and which of these relate to their perceptions of the affect expressed by the music. We also seek to identify acoustic features of the music which influence those perceptions. In this endeavour, we continue a long-standing theoretical tradition from Meyer [1] to Huron [2], in which it is envisaged that expectation (having a preconception of what the next events will be, based on general musical experience plus the experience of the piece to hand) is closely related to the perception of affect. Fulfilment of expectation is taken to be emotionally positive, and vice versa.

In pursuing this project, we focus on real-time measures of perception, in which listeners use a computer interface to continuously register their impression of either 'change in the music' (which they define for themselves), or the arousal and valence it expresses (see Methods). We then use these measures for statistical approaches using time series analysis, which is appropriate for temporal patterns of events which show serial correlation, meaning that recent events are partly predictive of the next event. Musical streams are serially correlated in virtually every respect; intensity, spectral properties, etc. In this presentation we try to minimise the technical elaboration of results, and refer the reader to detailed expositions we have given elsewhere of the use of time series analysis in music studies. The general principle to note is that an overall time series model of a data or musical series is a model of its continuing *process*, expressed throughout the piece (or throughout a segment chosen for separate analysis when appropriate).

The main musical pieces we have studied previously in this manner [3-5] are 3 minute sections of three works of electroacoustic music (by Wishart, Xenakis, and Dean), and one of atonal piano music (Webern). In the case of Wishart's *Red Bird*, we found that listeners' perceptions of musical change and of its expressed arousal were strongly predicted by the acoustic intensity profile; there were also interactions between perceptual variables (whereby change, arousal and valence perceptions might influence each other). We went on from this strong set of observations to undertake a 'causal' experiment, in which a segment of a Dvorak Slavonic Dance was studied for the relation between intensity profile and perceived arousal. We hypothesised that if intensity change was a dominant or strong influence on that perception, then by inverting the intensity profile (i.e. low dB became high and vice versa) of the piece we should invert the arousal profile: this was the case. The interpretation that intensity is a significant influence on perceptions of arousal was supported by additional studies with three other disparate pieces (one of tonal minimal music, one of atonal, and one of noise music), upon which we superimposed the original Dvorak intensity profile, as a result of which we were able to obtain arousal perception profiles which were related to the intensity profile [6].

It is important to note (with [7]) that features of a piece which are significant for musicological analyses are not necessarily significant for non-musician listeners, or even for musicians with limited familiarity with the piece or idiom. This is why our continuous perceptual parameter of change is potentially useful: if a musicological structure does not register in terms of change, then it is probably not influential for that listener. By extension, if there is a perception of change at a particular point in a piece, and there is some clearcut timbral or structural feature introduced at that point (perhaps, for example, the entry of a soloist in a concerto), then it is reasonable to consider whether a feature variable, representing the localised presence or absence of that timbre or performance *event*, might be influential in the models of perceptual response we develop. We have used this approach successfully in previous studies of Wishart, where for example, animate and human sounds are important statistical predictors of listeners' perceptions. We have also identified impacts of varying degrees of vocal quality in responses to music [3, 8]. In the present work we assess the possible impact of some of the obvious surface events in *Metastaseis*.

So in this paper, we provide some further analysis of perceptions of Xenakis's *Bohor* and compare them with new data on responses to his slightly earlier orchestral piece, *Metastaseis*.

2. MUSICAL SECTIONS STUDIED, AND METHODS

We present data in this paper concerning extracts from the two Xenakis works. The segments used are : *Bohor* (1962), the first 3 minutes (taken from the EMF release); *Metastaseis* (1953-4), the first two minutes, taken from the recording by the SouthWestGerman Radio Orchestra, conducted by Hans Rosbaud, in 1955 (from ADES CD 14.122.2 (1988)). We analyse the acoustic intensity (SPL, in dB, the unweighted physical property) and the spectral flatness (Wiener's Entropy, expressed on a log scale from zero to minus infinity) across each piece in short time windows (40msec). The spectral flatness of an infinitely thin spectrum is minus infinity, and that of white noise is 0. Thus, as noise content increases, so does spectral flatness. We also measure spectral centroid, and use certain specific qualitative timbral features in extending our analyses.

Our methods have been detailed previously [3, 5], and are summarised briefly here. In this paper we consider the perceptions of 16 non-musicians (university students) with respect to *Bohor*; our overall subject group ranged from 18-58 years in age (median 25.5). For *Metastaseis*, 22 non-musicians (university students) ranged from 17-34 years in age. They listened to the pieces on headphones while making continuous responses on a computer using a mouse. For the perception of 'change in the music', they moved the mouse at a rate corresponding to their estimation of the extent of change, and stopped moving the mouse when they heard no change. For the perception of affect, we use a two-dimensional interface with arousal (active to passive) on one axis, and valence on another bisecting the first, representing the positive to negative range. This 2-dimensional model (the Russell circumplex model [9]) and the interface have been used extensively in our earlier work and by Schubert and others [10, 11]. Presentation of the 'change in sound' and 'affect' tasks was counterbalanced.

The data (three acoustic time series variables and three perceptual time series variables) were analysed by time series techniques, appropriate for serial correlation. Univariate analyses use ARMAX (autoregressive moving average analysis with eXternal predictors). A univariate analysis is a model of one variable (e.g. perceived arousal), regardless of how many predictor variables (e.g. acoustic intensity, spectral flatness) it uses. Multivariate analyses are conducted by VAR (vector autoregression), and this permits treating all variables equally, such that their possible mutual influences can be assessed, and tested in a statistically principled way using Granger Causality. Granger Causality is an assessment of the power of the statistical relationship: strong Granger Causality is at least suggestive that there may be a causal connection, but it remains a correlation only. For technical reasons, it is often necessary to 'difference' a perceptual series for analysis: this means constructing a new series whose points are the successive values of the differences between successive points of the original. These are referenced here as Dseries, where series is the name of the variable in question. Once differencing is required, all series under consideration are differenced and Dseries for each is used in the statistical analyses. The statistical models are optimised by selection on the basis of the significance of individual predictors and the overall fit and parsimony of the analysis, to provide the best available model for predicting each variable. The Bayesian Information Criterion (whose value should be minimized) is the primary criterion used for model fit and parsimony. We do not detail these analyses here, but rather try to point out what it is they mean, and hence how they contribute to the interpretive argument.

3. RESULTS

Harley provides a valuable and informative introduction to the pieces we study [12]. It is perhaps appropriate to reiterate that *Bohor,* the electro-acoustic piece, is a relatively homogeneous piece, particularly in the section we have studied. While there are major spectral changes, intensity levels are rather flat, based largely on bell sounds. But nevertheless, in relation to the modest changes in intensity, taking the piece as a whole, the patterns display the archetypal form we have found in much electroacoustic music [13-15]), with short crescendi (rapid rate of change of intensity) and longer decrescendi (slower rate of change). Such patterns may have perceptual impacts, for example in maintaining attention [16]. In principle, small changes in a context of overall small change may be as influential as large ones in a context of large change. Later in the piece, as others have studied, there are varied derivatives of more diverse instrumental sounds, sometimes more obvious in origin than at the outset, and these may be perceived as strong acoustic/timbral features [17]. *Metastaseis*, for orchestra, comprises multiple massive glissandi, and much larger intensity changes than *Bohor*, including dramatic moments of temporary silence.

For perceptual studies, there is advantage in using stimuli which are unfamiliar, so that responses are not heavily conditioned by cultural expectation. For this reason, we previously assessed whether *Bohor* or its style was familiar to our participants [3]. We assessed this with a questionnaire which defined 5 levels of familiarity: the greatest familiarity being reflected as "I often listen to this piece of music", with the two least familiar categories being "I have heard something like this but not this piece before" and finally "I have never heard anything like this before". For our 16 non-musicians, 15 responded with the least familiar category, and one with the second-to-least

Table 1 compares the overall statistics of the acoustic features of the two pieces and the perceptual responses to them. The coefficient of variation (CV = standard deviation / mean) is an index of the overall variability of the time series. As for acoustic intensity patterns mentioned already, Table 1 shows that *Bohor* has low CVs in all respects in comparison with *Metastaseis*. As might be expected, the spectral flatness of the orchestral piece is lower than of the electroacoustic: this no doubt reflects the diversity of instrumental timbre at work throughout. A cursory consideration of the table indicates that intensity and spectral flatness might well be influences on the perceptual variables, because of the parallels between them.

Table 1. PARALLELS BETWEEN ACOUSTIC AND PERCEPTUAL PARAMETERS

Means (M) and Coefficients of Variation (CV) for the Intensity and Spectral Flatness Measures of the Xenakis Pieces

	Intensity (dB)		*Spectral Flatness (Wieners)*	
Piece	M	CV	M	CV
Bohor	60.53	0.04	-6.83	0.07
Metastaseis	65.53	0.14	-8.07	0.12

Means (M) and Coefficients of Variation for Real-Time Perceptual Ratings for the Xenakis Pieces

	Change in Sound		*Arousal*		*Valence*	
Piece	M	CV	M	CV	M	CV
Bohor	0.08	0.41	14.83	0.04	-6.32	0.08
Metastaseis	0.16	0.91	4.24	0.09	-26.43	0.19

Figures 1 and 2 also compare the two pieces in relation to the kinetics of intensity, change, arousal and valence. Figure 1 shows how the static nature of acoustic intensity in *Bohor* and its perceptual effects forms a clear contrast with the more variable features of *Metastaseis*. For *Bohor*, intensity and change apparently have slight relationship, but this is more pronounced for *Metastaseis*. Figure 2 shows that for both pieces, and particularly *Metastaseis* there is a degree of mirroring between arousal and valence. Note that later analyses show that this is not a significant direct relationship (in these cases) but in the case of *Metastaseis* at least it is an effect of intensity on both perceptual parameters.

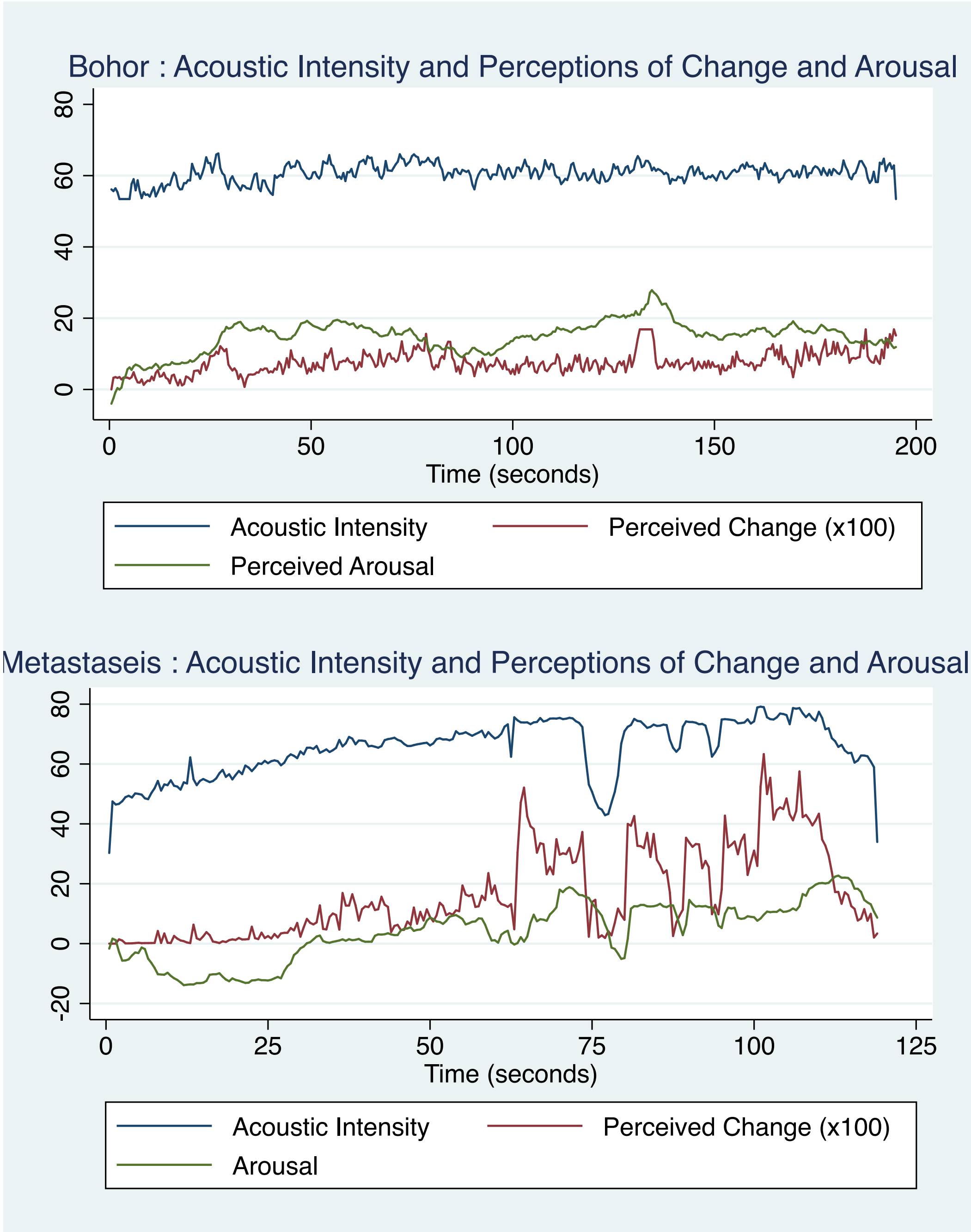

Figure 1. A comparison of the Acoustic Intensity and Change/Arousal profiles for Bohor and Metastaseis.

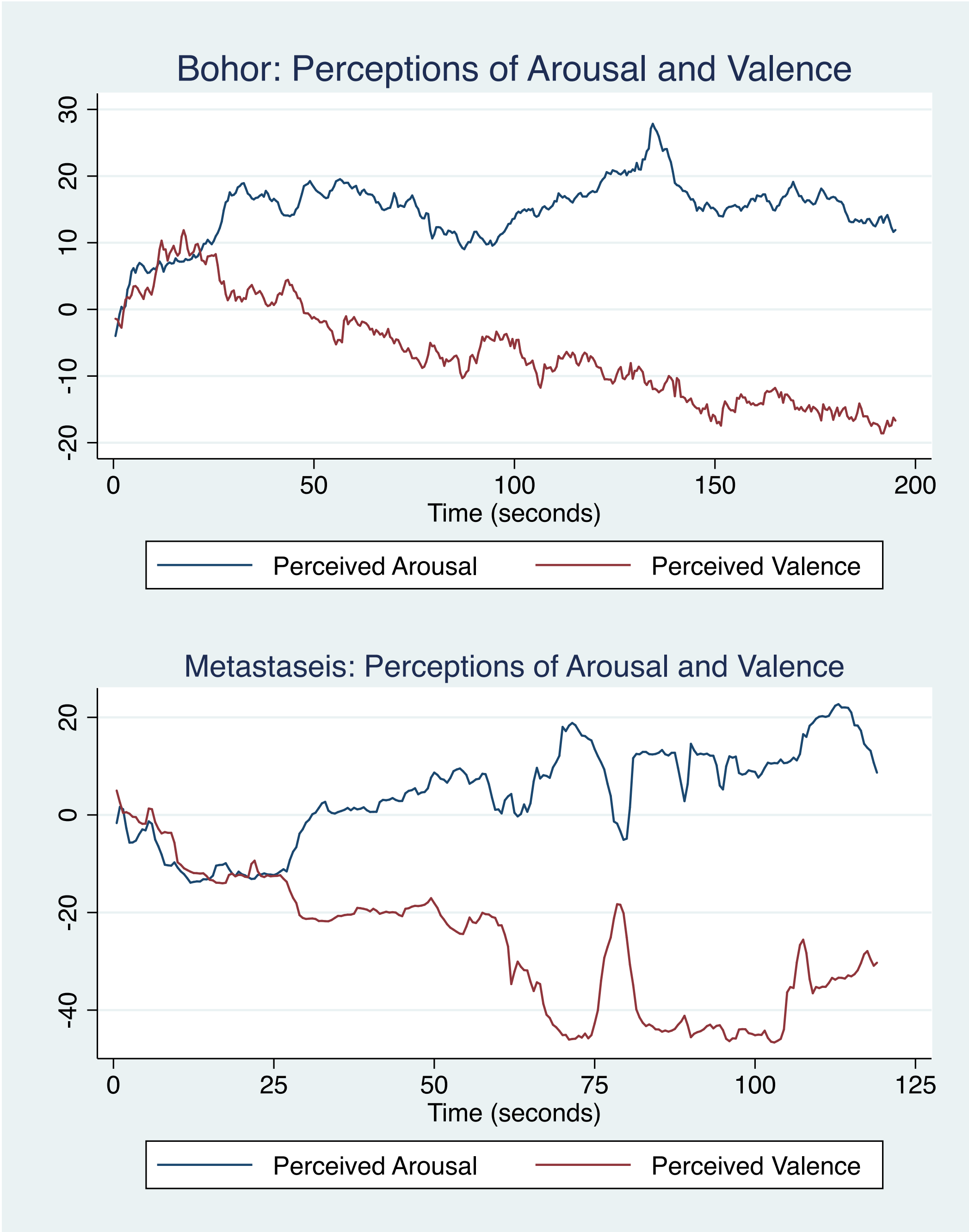

Figure 2. A comparison of the perceived affect time series for *Bohor* and *Metastaseis*.

Tables 2 and 3 present detailed VAR analyses of the two pieces. The variables modeled are listed under "Equation", and the characteristics of each model in terms of fit and probability are given on the same row. For *Bohor* (Table 2), none of the models are particularly good, the best being that for Dchange (the first difference of perceived change). Accordingly, the Granger Causality test only indicates this model as containing a significant predictor-response relationship between Dintensity and Dchange, as we have described previously. Spectral flatness was not a significant predictor.

Table 2. TIME SERIES ANALYSIS OF PERCEPTIONS OF *BOHOR* USING VECTOR AUTOREGRESSION

Equation	*Number of Parameters*	*RMSErrors*	*R-squared(fit)*	*chi2*	*P>chi2*
Dchange	10	.018181	0.16727	7.71739	0.0000
Darousal	10	.521227	0.13686	1.31157	0.0000
Dvalence	10	.814615	0.03521	4.1271	0.1673

Legend to Table 2: Vector autoregression (VAR) permits a statistical assessment of the mutual predictive influences amongst a group of variables, in our case three perceptual and two acoustic variables. The variables entered into the model were: Dchange, Darousal, Dvalence, Dintensity and Dspectral-flatness, and two autoregressive lags of each were used (dealing with the serial correlation in each data series). The interpretation of the table follows, using the Darousal row as example. Under 'Equation', Darousal indicates that the row defines parameters in the model of Darousal obtained within the overall vector autoregression. This model (in common with all the other component models) had 10 parameters used as predictors, and the next columns indicate how precise the fit was (how close the model predictions are to the observed data). RMSE is the residual mean sum of squared errors, a way of averaging the distance between each prediction point and each data point (lower is better); R-Squared (0.13686) is an estimate of how much of the variation in the variable being modeled (here Darousal) is explained by the model (it ranges from 0 to 1 and higher is better). The last two parameters go together to test the significance, that is to assess the probability of this degree of model fit arising by chance (for Darousal, almost zero). Again, low P values are supportive of a model, and values <0.05 are considered of interest. In summary we have here statistically meaningful models only of Darousal and Dchange, and these have poor fit. Correspondingly, tests of Granger causality are only significant for the influence of Dintensity on Dchange ($p < 0.000$).

Table 3 presents the corresponding analysis for *Metastaseis*, where the models for the perceptual variables are somewhat better (R-squared values of around 0.3). Correspondingly, both Dchange and Dintensity are Granger-Causal of perceived Darousal and both Dintensity and Dspectral-flatness are significant for Dchange (and in the full model it can be observed that Dintensity is more influential quantitatively). The perceived valence (Dvalence) in *Metastaseis* is quite well modeled, with Dintensity as the Granger-Causal predictor. This is interesting, as in most previous studies, even those which simply assess retrospective categorical comments, valence has been poorly modeled, meaning that predictor variables have not been well identified

Table 3. TIME SERIES ANALYSIS OF PERCEPTIONS OF *METASTASEIS* USING VECTOR AUTOREGRESSION

Equation	*Number of Parameters*	*RMSE*	*R-sq*	*chi2*	*P>chi2*
Dchange	10	.050706	0.3840	146.4909	0.0000
Darousal	10	1.50003	0.2685	86.2533	0.0000
Dvalence	10	1.38544	0.3103	105.7397	0.0000

Granger causality tests, indicating which predictors are significant in an equation

Equation	*Predictor*	*chi2*	*df*	*Prob > chi2*
Darousal	Dchange	7.9289	2	0.019
Darousal	Dintensity	9.1855	2	0.010
Dchange	Dintensity	109.56	2	0.000
Dchange	Dspectral-flatness	42.389	2	0.000

Dvalence	Dintensity	7.1546	2	0.028

Legend to Table 3. The interpretation of this table is as for Table 2. All three perceptual and two acoustic variables are entered into the model, together with two autoregressive lags. Here we also tabulate the significant Granger Causalities, where the specified 'predictor' is causal of the variable listed under Equation, and 'df' refers to degrees of freedom for the test of significance.

Given this modest success in predicting perceptual *processes* of *Metastaseis* on the basis of acoustic features, we also made a simple descriptive analysis of the key sonic/musical *events* in the segment under study (see Figure 3). Each of the features we identified as events was then tested for impact in the statistical models, by ascribing it a value of 1 for the period it is present, and 0 when absent. Table 4 summarises the results of this analysis using univariate ARMAX analysis; where a model is optimized separately for each perceptual parameter being modelled.

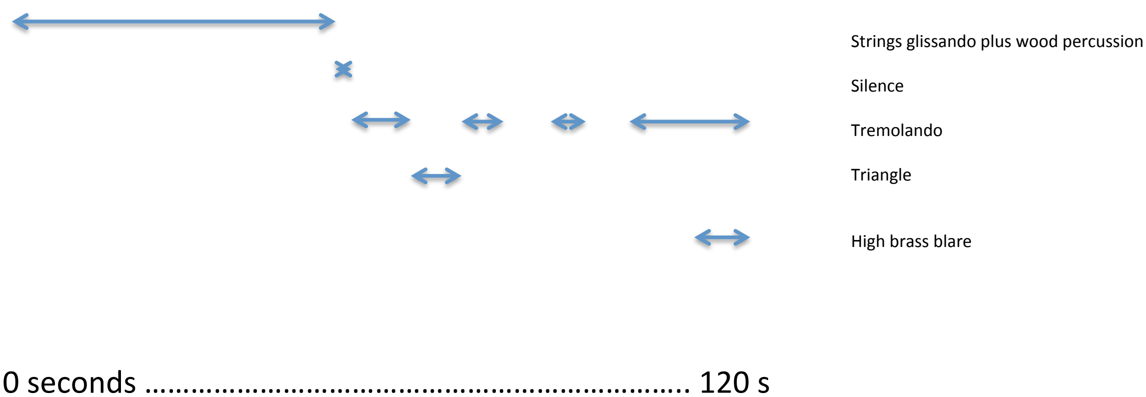

Figure 3. Events (motifs sonores) in the opening section of *Metastaseis* (roughly to scale).

Legend to Figure 3. Note that the large drop in arousal and increase in valence shown in Figure 2 coincides with one of the pulses of tremolando.

Table 4. TIME SERIES ANALYSIS OF PERCEPTIONS OF *METASTASEIS* USING UNIVARIATE ARMAX AND SONIC STRUCTURAL PREDICTORS

Models of perceived Dchange	
Basic Model predictors	*BIC*
lags1,2 of Dintensity; lags1,2 of D.spectral-flatness; lags 1,2 of autoregressive error; no constant	-702.98
Added Sonic Structural Predictor(s)	
lag 3 of silence	-712.96
lag 3 of silence; lags 1,2 tremolo	-721.18
lag 3 of silence; lags 1,2 tremolo; lags 2,3 triangle	-724.34
lag 3 of silence; lags 1,2 tremolo; lags 2,3 triangle, lags 2,3 high-brass	-728.94
Models of perceived Darousal	
Basic Model predictors	*BIC*

lags 1-3 of Dintensity; lag 1 of autoregressive error; no constant	879.05
Added Sonic Structural Predictor(s)	
lags 1,3 of triangle	878.31
lags 1,3 of triangle; lag 2 of silence	877.49
Models of perceived Dvalence	
Basic Model predictors	*BIC*
lags 1,2 of Dvalence; lags 1,2 of Dintensity; lags 1, 3 of autoregressive error; no constant	849.70
Added Sonic Structural Predictor(s)	
lags 1-3 of silence	819.52

Legend to Table 4. BIC (Bayesian information criterion) values are an index of model quality, assessing both fit and the number of variable predictor parameters required (and penalizing for them); lower values are better, and differences in BIC of >=4 are highly significant. BIC values for models of different variables (e.g. Dchange vs Darousal) cannot be compared with each other, but only BIC values for different models of the same variable (and dataset). For the models of Dchange, the final one represented above was not worsened by the removal of Dspectral-flatness as predictor (thus its impact could be subsumed by the sonic structural variables added). The models of Darousal are not significantly distinct, as judged by the BIC values.

Overall, Table 4 shows that for perceived Dchange, each individual sonic/timbral feature from Fig. 2 was a significant (cumulative) contributor to perceived change: they partially replaced spectral flatness in predictive impact, and spectral flatness was not required for the final model listed for Dchange. Intensity remained important. For Darousal, tremolo and silence were only weak cumulative predictors, marginally enhancing the model based on intensity and autoregression. This suggests that intensity largely subsumes the impact of the structural variables on arousal. For Dvalence, silence was a strong predictor (though it could not totally replace intensity), but no other features were. As mentioned already, we showed previously that our participants were unfamiliar with *Bohor*, and unfamiliarity with consequent lack of perceptual fluency might predict (initial) dislike (discussed in [3]). The positive valence response to the periods of silence might even be nothing more than a trivial expression of the removal of the disliked sound. As we noted, understanding continuous perceived valence is much less advanced than understanding perceived arousal.

4. DISCUSSION

Our results here confirm the significant impact of acoustic intensity upon perceptions of change and affect in electroacoustic music, including that of Xenakis. We have also noted that at least some of his music presents a pattern of short crescendi and longer descrescendi, features of the musical dynamics that we have found to be generic amongst electroacoustic music. Indeed, both these features apply to classical instrumental and orchestral music. For example, as mentioned, in a causal intervention study we showed that intensity can drive perceptions of arousal expressed in a Dvorak orchestral work; and in unpublished extensive studies of music by Haydn, and to a more limited extent Beethoven, we have also recovered the same generic statistical intensity patterns.

Thus it was of particular interest here to begin to compare Xenakis's instrumental and electroacoustic music. Our data on this are clearly no more than a very modest start to this endeavour. In particular, it may be that the section of *Bohor* we have chosen is amongst the more acoustically homogeneous in Xenakis ea work, though careful listening to *La Légende D'Eer* and several other pieces would not suggest that. Conversely, it may be that the dynamic opening section of

Metastaseis is unusual amongst his work: but again careful qualitative listening would not indicate that. So it is worth discussing some of the features and distinctions we found in the perceptions of these two pieces.

Most obviously, listeners' perception of extents and rates of change in the music bore a good correlation with the measured extents of acoustic variation, particularly of intensity. This is perhaps not surprising given our previous work, and indicates that acoustic intensity change may be a general, even cross-cultural, cue for music perception, in that it has been described as widespread in many if not all musics, and is clearly perceptible even to those unfamiliar with a particular music culture or genre [18]. In other studies, we are assessing whether intensity remains an important factor even in those musics such as ambient music that might be considered to minimise intensity change. Conversely, it is notable that acoustic intensity in recorded popular music such as rock has gradually increased over the last few decades [19] such that the range has narrowed and focused on quite high dB: whether this has changed the impact of acoustic intensity on the perception of change and affect also requires consideration. The importance of acoustic intensity to Xenakis himself is obvious in his well documented penchant for projecting his electroacoustic pieces at very high volume (see for example, [12]). As our editor notes on the sleeve notes to the EMF recording, Pierre Schaeffer, in whose GRM studios Xenakis worked at the time of *Bohor*, comments wryly about the piece, referring to its 'offensive accumulation of lancet jabs to the ear at maximum volume level' (in Harley's translation).

When we turn to the perception of affect, as one might expect the situation becomes more complex. The responses to *Bohor* are poorly modelled: perhaps an approach relating to the 'deeper' acoustic and musical structure is needed to address this. As musical scientists, our first target needed to be the more obvious and accessible surface structure, and it is well known that many features of perception of phrase segmentation operate at this level [20, 21]; however, this should not prevent us from delving further in the future. In the case of *Metastaseis,* the responses were richer, and our modelling was moderately successful. Strongest was the evidence on the perceived arousal of the music, suggesting that acoustic intensity change was again important, but that it can act in tandem with the apparent surface features such as the string glissandi, tremolo, silence, brass. This interpretation coheres with our previous study of Wishart's *Red Bird*, in which sounds of animate and human origin were of importance.

However, an important distinction between *Metastaseis* and *Red Bird* occurs for valence: for it is in this context that animate and human sounds influence perceptions of *Red Bird*, whereas with the valence of the Xenakis piece it was only the burst of silence that was a clearcut statistical influence. As noted above, our non-musician listeners were unfamiliar with *Bohor*, and probably with *Metastaseis* too, so this response may simply represent a reduction in level of dislike. Studies of the influence of specific structural features, such as the described playing and instrumentation features in *Metastaseis*, need to be developed much further, so that they can encompass 'agency' and its expression in the pieces. By this we mean not only the interpretation of the piece in terms of its origins in effortful human actions, or movements of physical objects, as in our FEELA hypothesis [15], but also the agonism of the debate between a soloist and orchestral accompanist in a concerto, or that between first subject and its development in a classical sonata. While there is evidence that non-musicians are not explicitly aware of such features even within tonality (e.g. [22, 23]), their implicit effect has not yet been properly explored.

More broadly, we consider the continuing difficulty in understanding what shapes perceptions of valence to indicate a lack of assessment of the appropriately influential variables as yet. Some models which seek to predict the overall affect (arousal and valence) of chunks of music, for example with artificial neural nets, have been reasonably successful, but mainly by including very large numbers of variables, and training extensively on simple responses [24]. These models are not readily interpretable in terms of specific causal effects of individual components, since the net ‘logic’ is not readily accessible without further quite complex general effects analyses [25], which are yet to be done.

Two distinct approaches seem to bear promise for future studies of musical affect. One is the development of an information theoretic approach, in which music is considered to consist of large but finite ‘alphabets’ of component events (e.g. pitch, duration, timbre), whose sequential probabilities can be assessed and used for predictions This has given good success in predicting expectations, that is what notes might appear next in an instrumental piece, or when a phrase might end [26]. It has yet to be applied substantially to issues of affect [4, 27]. Furthermore, to develop an appropriate alphabet for electroacoustic music requires a reductive, sparse sampling approach, in which the frame by frame (44.1 thousand samples per second on a CD) spectral complexity of the music can be reduced to a manageable scope. This production of a symbolic description of the music might be approached by means of the sequencing of spectral properties such as the MFCC (mel-frequency-cepstral-coefficients), but will require considerable development.

The second approach, perhaps particularly relevant to valence, is the consideration of the interaction of musical familiarity, the personal degree of self-absorption which for example is stronger in creative dancers than non-dancers [28], and the transiently changing engagement that the music induces in a listener. Measuring this will not be easy, though initial attempts have been made in our lab [29]. Perhaps the degree to which musical listening engages a person is then a significant factor upon their perceptions of valence, both in its extent and direction of change. It can be expected that a non-musician presented with unfamiliar music may often find it difficult to engage with. Widely held educational ideals suggest this can be overcome, and an empirical understanding of the relationship might encourage and facilitate the appropriate educational efforts (at all stages in life).

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