Analysis of acoustic emissions from polymers

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Acoustic emissions obtained from polymers under stress have been subjected to various mathematical analyses with the objective of relating the observed signals to accompanying chemical and physical changes in the polymer. The following methods have been investigated: frequency analysis, autocorrelation analysis, cepstrum analysis and cluster analysis (pattern recognition). It is shown that it is possible to classify the signals from a given polymer sample into relatively few types and that there is a periodicity in a number of plots of acoustic power vs time. Differences between samples are evident, although it is not possible at this stage to state that they are statistically significant. The materials examined include, nylon-6,6, 'Diakon', polypropylene and various composites.

Keywords Acoustic emissions; stress; mathematical analysis; nylon-6,6; Diakon; polypropylene; composites

INTRODUCTION

Earlier, we described the experimental arrangements for the generation and detection of acoustic signals from polymers and composites and provided some evidence from e.s.r. spectroscopy which suggested that there is an association of acoustic and molecular events[1]. It is doubtful if the relationship is a simple one; it is more likely that a sequence of different molecular and mechanical events gives rise to a particular acoustic signal. It is also likely that a different sequence of events might result in a totally different acoustic signal. For example, microcrack generation by a free radical propagation of a broken bond, as proposed by Zhurkov[2], is expected to produce a different pattern of acoustic energy release than mechanical slippage. There is a clear need to analyse the experimental results in such a way that these differences are made evident.

Other workers have carried out frequency analysis, usually via Fourier transform[3–8], and Speake and Curtis have proposed a rationalization of this analysis to follow the change, during mechanical tests, of dominant acoustic frequencies[6,8]. Elsley and Graham have described a pattern recognition procedure for the classification of transient emissions[9]. We have extended these studies and investigated additional standard methods of signal analysis. In this paper we report preliminary findings of (a) periodicity in plots of acoustic power vs. time (autocorrelation analysis), (b) frequency and echo analysis of individual acoustic emissions (Fourier transform and cepstrum analysis) and (c) classification of individual signals by cluster analysis. Each mathematical procedure is briefly described and the results obtained with it are shown and discussed.

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EXPERIMENTAL

Apparatus

The stresser and basic apparatus have been described previously[1]. The data collection system has been modified by the inclusion of a DataLab DL920 transient recorder, a DEC MINC II microcomputer and Tektonix 4662 digital plotter, arranged as shown in *Figure 1*. It was used to collect individual events or signals which for convenience are defined as those occurring within a period of 100 μs. These were recorded in 1024 channels on the transient

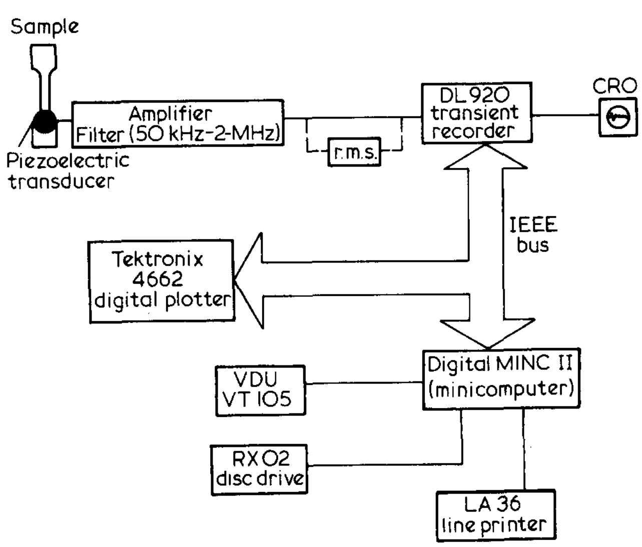

Figure 1 **Block diagram of data acquisition and processing system**

recorder and then transferred to the computer, ultimately to be stored on discs.

The signal analysis except for the pattern recognition was performed on the MINC II operating in Basic mode. The pattern recognition analysis was carried out on ICL 1900 mainframe computer.

Samples

The samples used were described earlier[1].

Procedures

Generation and collection of signals. The sample was placed in the stresser and a fixed load was applied. Signals were detected on the transient recorder and transferred to the computer, if they were judged to be above background. Sixty-four signals were collected at each load, it being judged that this number was reasonably representative. Then the load was increased and the process repeated until either the fracture point or some predetermined load level was reached.

Signal analysis

Except for the pattern recognition, programs were written by making use of standard routines in the MINC II library.

Autocorrelation analysis. Procedures for autocorrelation analysis are described and discussed by Horlick and Hieftje[10] and Chatfield[11]. Computer programs were written to permit analysis as described in these articles, an option being given to retain or remove a linear, multiplicative or integrated trend[12].

Frequency analysis. The fast Fourier transform (FFT), which is standard in the MINC II, was used as the basis for frequency analysis.

Cepstrum analysis. The programs were written to permit cepstrum analysis as described by Bogert *et al.*[13] and Kemerait and Childers[14].

Pattern recognition (cluster) analysis. A program was written to carry out the compound classifier method as described by Batchelor[15], the results being projected into a two-dimensional representation by the method of Kowalski and Bender[16]. A full description is given by Lilley[17]. The program was written in Fortran IV and executed on an ICL 1904S mainframe computer.

RESULTS AND DISCUSSION

Analysis of frequency of acoustic events

Autocorrelation. Autocorrelation is a means of testing the periodicity of a given signal, being a relative measure of the correlation between a signal with itself when displaced in time. The correlation function, $C_{aa}(\tau)$, is determined by evaluating the time-averaged product of the signal with a time-displaced version of itself[10], and is given by:

$$C_{aa}(\tau) = \lim_{T\to\infty} \frac{1}{2T} \int_{T}^{T} a(t)a(t \pm \tau)\,dt$$

where $a(t)$ is the signal at time t *and* τ is the time displacement. The function can have a maximum value of $+1$, which indicates complete correlation and a minimum value of -1, which indicates that the signal is 180° out of phase with itself. A value of zero indicates no correlation and this should be obtained if the data are random. In practice, the correlation found is only taken as significant if the function is greater than 0.2. There are complications if the signal is non-stationary, that is, if the mean and/or the variance change with time, for example if the signal has a rising background. Provision is made in the program to allow for this. Also it was decided to take the r.m.s. voltage of the transient signal, rather than the whole signal, so as to achieve a reasonable sampling rate.

An example of the autocorrelation of an echo with a signal is shown in *Figure 5*. Autocorrelations for event vs. time plots usually indicate slight correlation. Most work was done with glass-filled nylon samples since they were the most prolific sources of acoustic emissions, and also provide almost stationary signals (i.e. mean and variance and constant). From some polymers, the frequency of emissions is so low as to make any correlation doubtful and from others the variety of signals makes it difficult to have confidence that the requirement is met for the analysed data to be obtained under stationary conditions. Nevertheless, the correlations obtained did not conform to those expected for random data, and it is concluded that further work along these lines might well prove the existence of repeat patterns in the traces of acoustic emissions. The method may also be applied to the analysis of individual signals to differentiate overlapping signals or echoes.

Analysis of individual acoustic events

The rest of the paper is concerned with the analysis of individual signals collected over a 100 μs time span. It will be evident from the examples shown in *Figure 2* that the signals are of diverse types. The objects of the analysis are (a) to categorize the types of signal and (b) to see if there is any useful association between signal type and physical behaviour of the polymer. One of the major problems is to describe the immense amount of data by a few, easily measured parameters.

Frequency analysis. The frequency analysis for an individual signal was performed routinely by the FFT program, and the results were displayed as the power spectrum. Some typical results for 'Diakon' and 30% glass-filled polypropylene are shown in *Figure 3*. Since from each sample of 'Diakon', at each load, 64 signals were collected, various ways of presenting the results of the frequency analysis in a concise form were explored. The most useful representation of the data was the median frequency[3]. It has the advantage that it is extremely easy to compute, but the disadvantage that it may fall between two peaks in the power spectrum. The value of it is shown in the distribution of median frequencies for a given polymer sample (*Figure 4* and *Table 1*). For most samples the median frequency serves to define the signals, and it is evident that usually the signals from a particular sample are grouped rather than randomly distributed.

Cepstrum analysis. Cepstrum analysis provides a means for detecting echoes in a signal. It is widely used in seismography and it was thought that it might with advantage be applied to polymers to provide a check on the validity of the data and to offer a means of pinpointing the origin of an acoustic event.

The basic concept of the cepstrum is that, after a

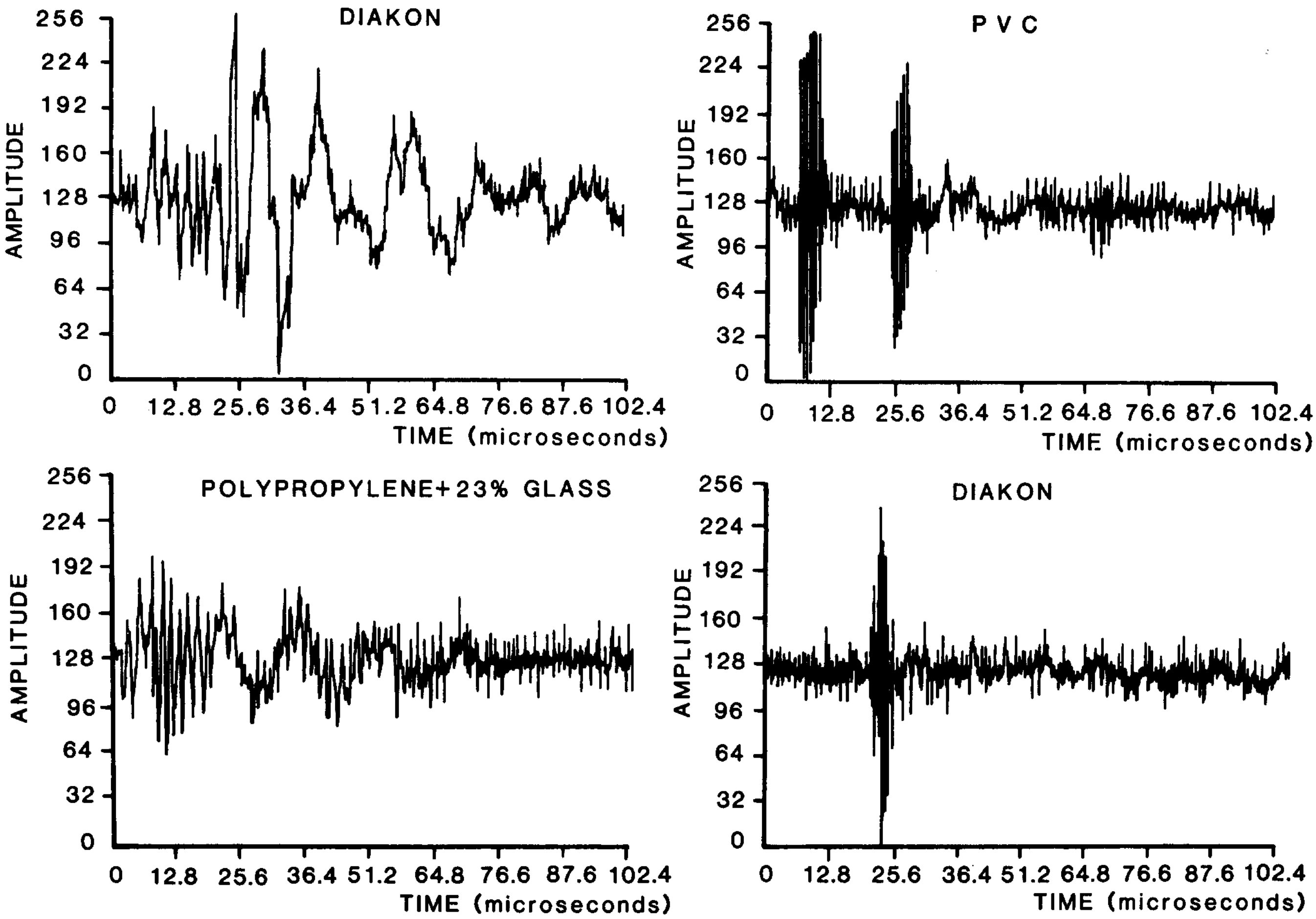

Figure 2 A selection of acoustic signals from polymers under stress to illustrate their diversity

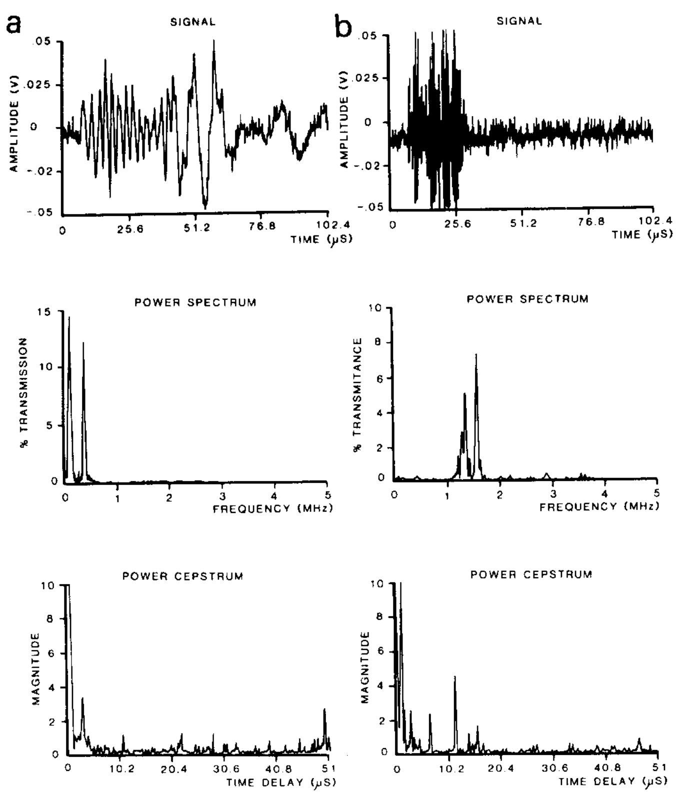

Figure 3 Representative signals, power spectra and cepstra: (a) 'Diakon', (b) polypropylene + 30% glass

Fourier transform of a signal and echo, the two are not separated because the echo is of the same frequency as the signal. However, the log of the square of the Fourier transform (i.e. log of the power spectrum) has separate terms for the signal and echo. Thus if a Fourier transform is performed on the log of the power spectrum, separate peaks will be observed, corresponding to the same frequency but displaced in time. The amplitude will also reflect the relative intensities of the original signal and echo. To distinguish from the power spectrum, Tukey[13] named the resulting spectrum a 'cepstrum' and the independent variable 'quefrency', to be measured in units of time. The basic relationships for the method are given in *Table 2*, and examples of their applications in *Figures 3* and 5. The time delay of the echo is given by the quefrency of the peak. It is to be noted that whereas the autocorrelation gives some indication of an echo, the cepstrum gives a measure of relative intensity and a better indication of the time delay.

When the procedure was originally devised, the computing time involved in its application was prohibitive, but now it can be performed rapidly with results such as those shown. The variation in echo distribution from sample to sample (*Figure 6*) indicates that the signals received are coming from different parts of the sample and that it is not, by some artifact of the apparatus, collected from the same spot. It also, by virtue of the amplitude, enables echoes to be distinguished from two separate signals emitted at almost the same time. Echoes also

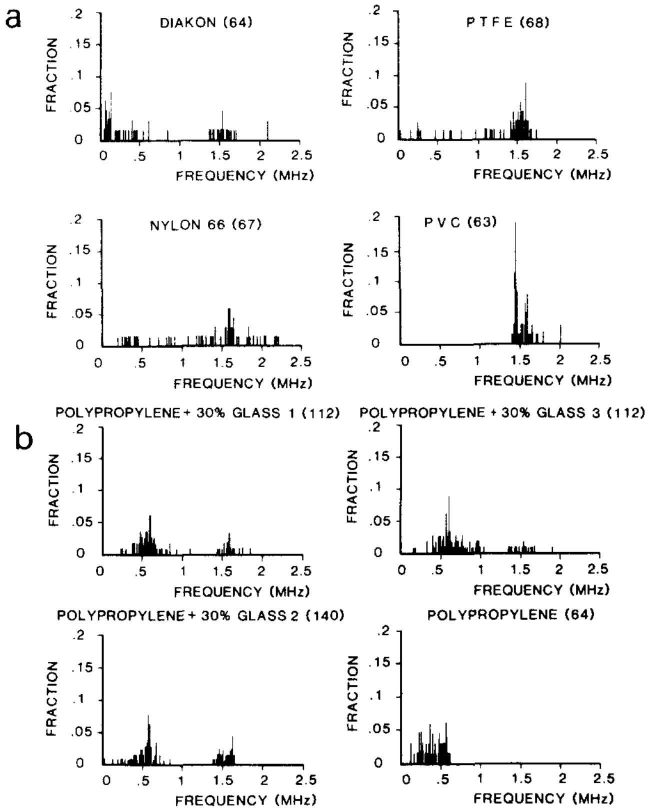

Figure 4 **Median frequency distributions for a number of individual signals from different stressed polymer samples: (a) Diakon, nylon-6,6, PTFE and PVC; (b) polypropylene + 30% glass (for three different types of filler glass) and polypropylene. (Figures in brackets are the number of individual signals analysed. See text for validity of signal at 1.5 MHz)**

contain within them spatial information and those arising from the shear wave also contain information about the nature of the sample, but so far we have not attempted the analysis required to extract this additional information.

Cluster analysis (pattern recognition). Pattern recognition analysis seeks to find useful relationships or groupings among complex data. There are various subdivisions of the subject[18,19], the one described below being cluster analysis. It enables associations to be found in multivariate data and permits use of ordinal (ranking) and cardinal (numeric) parameters. Thus it is perfectly feasible to include as variables, type of sample, batch number, age of sample, mechanical test data, acoustic emission data, and some application parameters, such as daily exposure to sunlight, average daily temperature, etc. It is our long-term objective to seek correlations with such parameters, but first it has been applied to the analysis of acoustic emission signals.

There are numerous possible methods[15,16,18–20], the one selected being the compound classifier centroid clustering method as described by Batchelor[15]. The principle of the method is illustrated in *Figure 7*. A two-dimensional array of data is shown, but the method is applicable in principle to any number of dimensions. In practice, up to 12 variables can be handled routinely by the most common mainframe computers. The procedure consists of finding the two nearest points and replacing them with one point, as their centroid. The procedure is repeated until all of the data are reduced to one point. At each step the distance between the points which are combined is noted and the process can be represented as a dendrogram, as shown in *Figure 7*. If the data fall into clusters, intra-cluster distances will be smaller than inter-cluster distances. Some judgement is made on the basis of the dendrogram as to how many clusters there are and what their position is in space, i.e. their locate. The locate, as indicated in *Figure 7*, is the centroid of a possible cluster. After locates are designated, the computer is able to re-examine the original data, place them into the

Table 1 The mean and the standard deviation of the median frequencies of the various samples examined

Sample (no. of signals in parentheses)	Mean of median frequencies, $\bar{f}_{med}$ (MHz)*	Standard deviation, σ	Per cent of total signals†
Diakon (MG102) (64)	0.21 1.51	0.14 0.08	55 35
Diakon + 20% rubber (61)	1.53	0.05	86.2
Diakon + 23% rubber (76)	1.64	0.09	97.4
X + 23% rubber (44)	1.63	0.51	88.6
Nylon-6,6 (67)	1.58 (1.59)	0.20 (0.04)	67.1 (37.3)
Nylon-6,6 + 33% glass (104)	0.56 1.58	0.07 0.08	86.5 13.5
PTFE (68)	1.50 (1.54)	0.14 (0.06)	82.3 (70.6)
PVC (63)	1.52	0.09	96.8
Polypropylene + 30% glass 1 (112)	0.56 (0.54) 1.58	0.12 (0.07) 0.08	75.9 (65.2) 22.3
Polypropylene + glass 2	0.54 (0.55) 1.54	0.13 (0.08) 0.07	67.8 (60.0) 32.2
Polypropylene + glass 3 (112)	0.63 (0.59) 1.54	0.13 (0.07) 0.13	84.8 (57.3) 15.2
Polypropylene + 40% $CaCO_3$ (63)	1.27 (1.24)	0.15 (0.10)	69.8 (60.3)
Polypropylene + 40% talc (88)	1.43 (1.47)	0.16 (0.08)	82.9 (65.9)

* For some sets of data, e.g. nylon-6,6 (*Figure 6*), different judgements may be made with respect to the width of the cluster of signals around the mean. Alternative possibilities are included in parentheses, in the $\bar{f}_{med}$, and per cent columns of the table
† Per cent of total number of signals falling within $\bar{f} \pm 2\sigma$

Table 2

Function	Signal	Signal + echo
Time signal	$y(t)$	$z(t) = y(t) + y(t-\tau)$
Fourier transform	$Y(\omega)$	$Z(\omega) = Y(\omega)(1 + e^{-i\omega\tau})$
Power spectrum	$\lvert Y(\omega)\rvert^2$	$\lvert Z(\omega)\rvert^2 = \lvert Y(\omega)\rvert^2(1 + 2\alpha \cos \omega\tau + \alpha^2)$
Log power spectrum	$2 \ln \lvert Y(\omega)\rvert$	$2 \ln \lvert Z(\omega)\rvert =$ $= 2 \ln \lvert Y(\omega)\rvert + 2\alpha \cos \omega\tau + \alpha^2$

$y(t)$ is the signal at time t, $z(t)$ is the signal plus echo, $Y(\omega)$ and $Z(\omega)$ the Fourier transforms of y and z in the frequency (ω) domain, τ is the echo delay time and α is the magnitude of echo

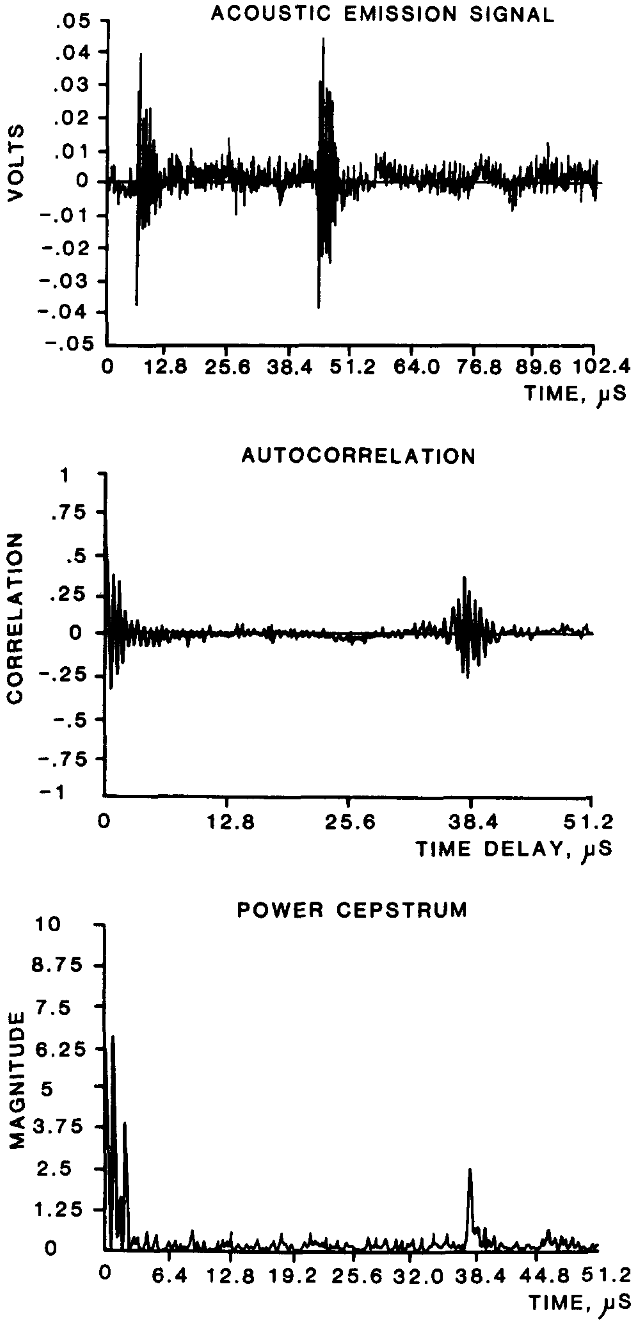

Figure 5 An acoustic emission from stressed nylon + 23% rubber with corresponding autocorrelation and cepstrum

appropriate cluster and compute the goodness of separation between clusters. An essential part of the method is that the experimenter makes an evaluation of the results at the dendrogram stage, but that is supported by further calculation. The process can be repeated until the experimenter is either satisfied with the result or concludes that further computation is not likely to lead to improvement.

In order to apply the procedure to the classification of acoustic emissions, some appropriate parameters had to be selected. After some experimentation it was found that the maximum amplitude, the median frequency and the variance (rather than the mean square amplitude) were satisfactory. Some results are shown in *Figures 8* and *9*.

Examination of these figures shows that for both polymers the acoustic emissions can be grouped into relatively few classes. For a given polymer, some groups are close together, and they have common features. They serve to illustrate the point that some human judgement is required to determine locates. (The degree of similarity appears greater than it is, because the diagram is a two-dimensional projection of a three-dimensional array. All of the standard tests show that the groups as shown are distinct.)

It also appears from *Figures 8* and *9* that the types of signal obtained from the two polymers differ. Our preliminary experiments suggest that this is a fair observation. It does seem that the same material reproducibly gives a set of characteristic acoustic signals. By cluster analysis, it is possible to distinguish between polypropylene, polypropylene + 30% glass with coupling agent, and polypropylene + 30% glass without coupling agent. Work is in hand to evaluate these initial findings critically.

A full appraisal of the applicability of cluster analysis to acoustic emissions will require a much longer study. However, there is little doubt that the employment of a multivariate sorting process guides the experimenter to make associations which would be impossible if only one variable were investigated. After classification, a visual examination of the data has always confirmed the validity of the cluster analysis. It is doubtful if similar results could have been derived by inspection alone. However, the procedure is purely mathematical, and there is not necessarily any physical significance in the groupings.

There are some mathematical problems associated with the technique also. The one which has caused most difficulty in this study has been that stemming from a predominant parameter. All parameters have to be normalized and scaled so as to ensure that each exerts a discriminatory effect. Nevertheless, this was not always sufficient. For example, if load, maximum amplitude and median frequency were used as parameters, then the groupings were essentially a series of linear plots of amplitude against median frequency for each level of load. Thus, it is prudent to view the cluster analysis as an interactive computer-assisted means of evaluating data. It seems to be a powerful method, even if few parameters and relatively few data points are used.

Validity of results

Since there is no way of predicting precisely what acoustic emissions are to be expected from a sample, there is no way in which spurious results are readily detected. There is in sharp contrast to spectroscopic methods where an impurity or malfunctioning instrument gives rise to additional distinctive bands in the spectrum. In acoustic emission work the problem is acute if conventional ring-down[21-23] or other event-counting techniques are employed, for the whole trace looks like a series of 'noise' spikes.

In this study a number of basic precautions were taken—mains filters have been used, the apparatus is tested before application of load, and noise is either offset before the experiment begins or, if it is excessive, the source of noise is detected and eliminated, etc. Additionally, different microphones have been employed, and it has been found that the results are consistent. Similar signals, but of different frequency, have been obtained from chemical reactions which have been monitored with the apparatus[24]. These have led us to conclude that the results obtained with the apparatus are genuine.

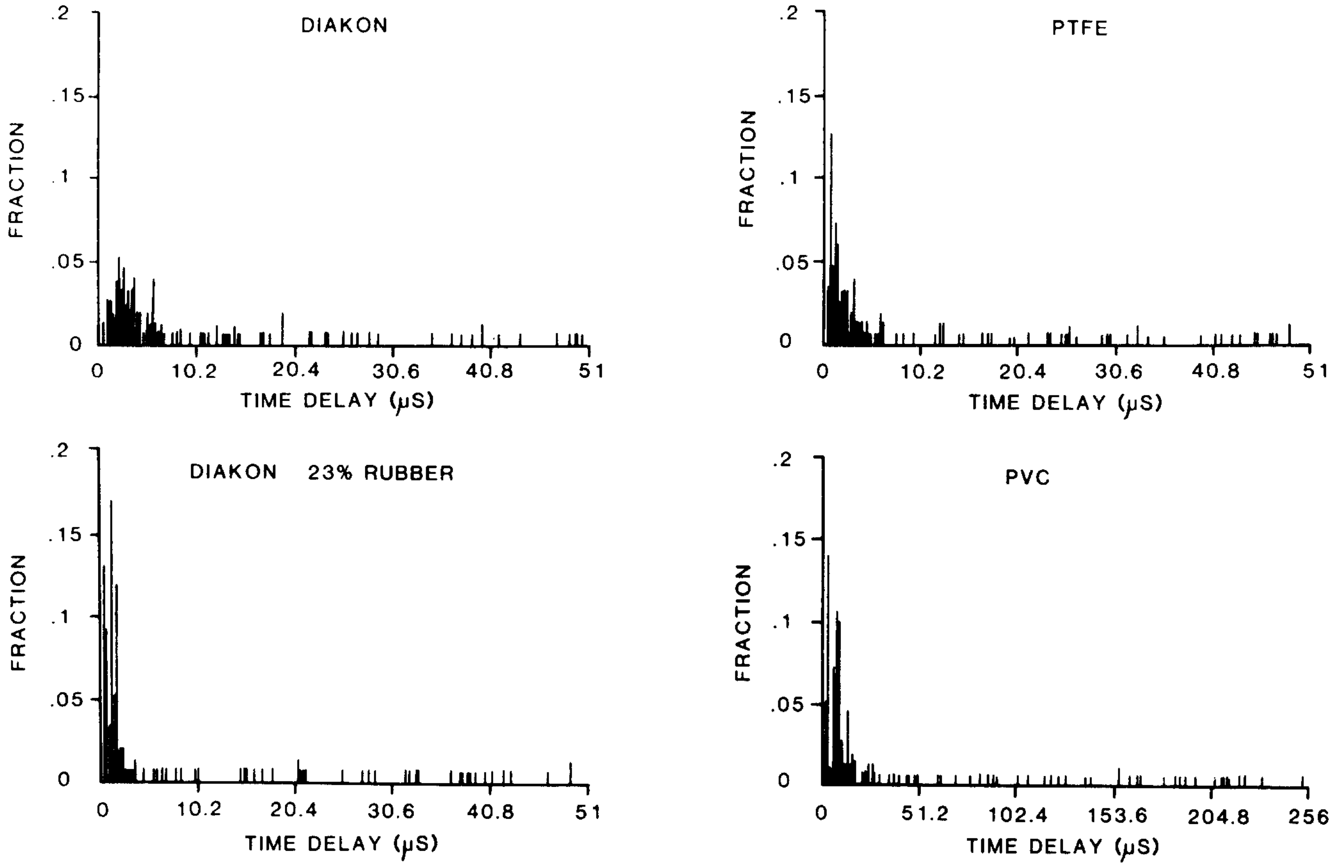

Figure 6 Distribution of echoes of acoustic emissions from different samples of stressed polymers. Each individual signal in the batch of signals (64) obtained from one polymer sample has been subjected to cepstrum analysis and is shown as a time delay relative to parent peak. Then the distribution of the major peaks in the resulting cepstra has been calculated and is shown, i.e. each distribution results from 64 signals obtained from one sample. Some signals have been subjected to an autocorrelation analysis

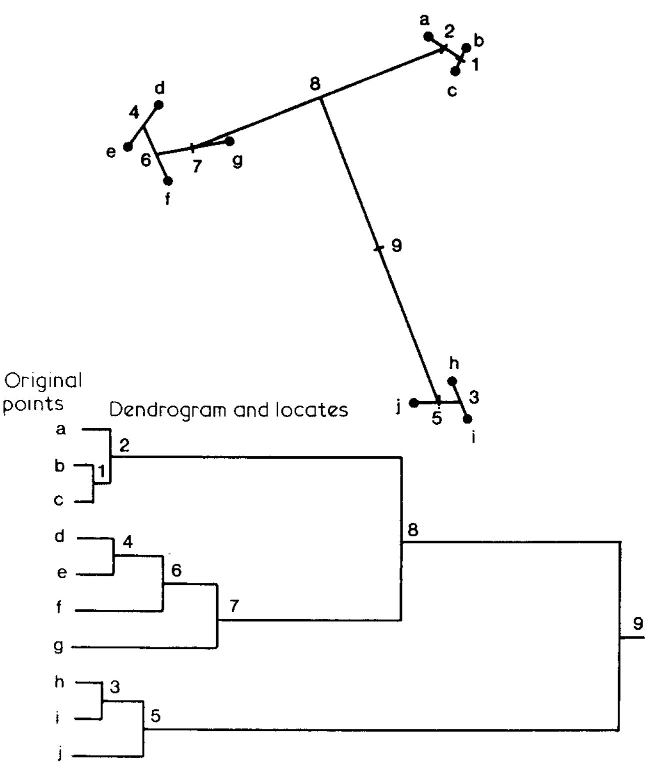

Figure 7 Schematic procedure for cluster analysis. Original data points are shown as letters a–j, and the sequence of joining nearest neighbours and replacing them by their centroid is shown numerically. The dendrogram is shown below, the lengths of each branch being approximately proportional to the distance between the points or locates being joined. By inspection, 2, 7 and 5 are taken as possible locates for clusters a–c, d–f and h–j respectively

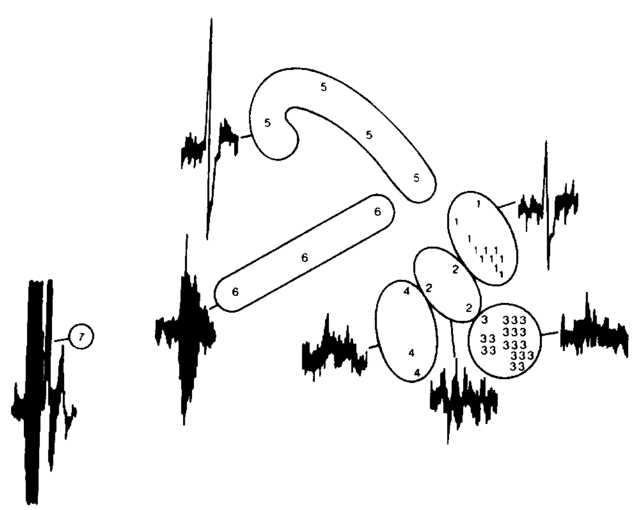

Figure 8 Results of cluster analysis of 64 signals from a sample of propylene + 40% calcium carbonate. (For each cluster the boundaries and a representative signal are indicated)

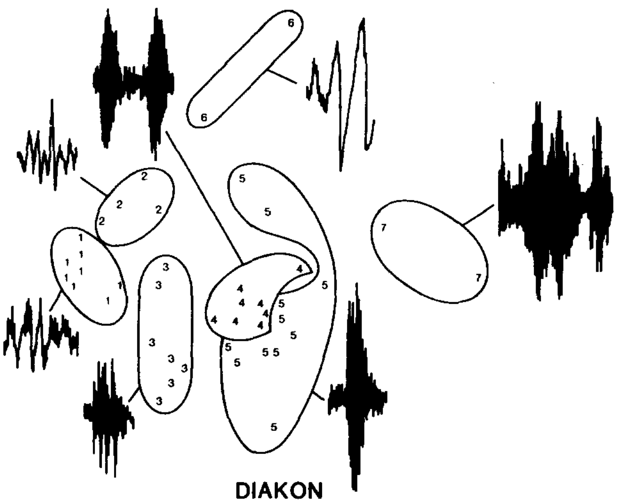

Figure 9 Results of cluster analysis of 64 signals from a sample of 'Diakon'. (For each cluster the boundaries and a representative signal are indicated)

Distributions of the variance, frequency and amplitudes of batches of signals have been examined and these suggest that the experimental procedure excludes rogue results and is reliable. The validity of the signal analysis procedure was provided inadvertently when it was employed to detect an infrequent but regular noise signal and to identify it as originating from the computer.

CONCLUSIONS

There are well attested associations between the rate and intensity of acoustic emissions and mechanical failure of various materials[21–23], but the application of the technique has been limited on the one hand by the lack of reliable and useful theory and on the other by the problem of extracting analytical information from the data. The methods described above may well help on both counts.

From the analytical viewpoint, it seems that the pattern recognition method is a powerful one. It is flexible, so that a variety of parameters can be incorporated and the complexities of the sample can be taken into account. The method of cluster analysis described above falls into the category of 'unsupervised learning'[19], whereby associations are sought within a given set of data without any *a priori* assumptions about the number of classes that exist. The category of 'supervised learning' is that in which the classes are defined and the object is to place the test signal into a predetermined class. It might be, for example, that for a given polymeric material the classes corresponded to 'exceptionally good material', 'average' and 'substandard', and possibly that these were subdivided according to particular strengths and weaknesses. Such information, if reliable and easily obtained, would obviously be of analytical value, and it is a logical development of the cluster analysis approach described above.

The cluster analysis also seems of importance in seeking physical explanations of acoustic emissions. It seems plausible to assume that particular types of acoustic emission and possibly patterns of acoustic emission are associated with specific types of degradation process. It is noteworthy that acoustic emissions from complex chemical reactions are quite reproducible and appear to be characteristic of the reaction[17]. Investigation of this hypothesis will be aided by the methods described here and especially if they are used in conjunction with each other and with other methods. We are currently working along these lines.

There is, however, a time constraint on this type of analysis. In this study, the frequency analysis, amplitude and cepstrum analysis with printout for a batch of 64 signals takes about 40 min. The pattern recognition exercise takes longer, with the need to make at least two separate entries to the computer and to analyse the output. Because of the time-sharing arrangements on our mainframe computer, a complete analysis may, at present, spread itself across a week. Recently the process has been improved so that acoustic data can be collected and processed within the time span of a typical mechanical test.

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