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On Aids to Interpretation in Monitoring Civil Engineering Systems

Aides pour la surveillance de systèmes en génie civil

Über Hilfsmittel bei der Auswertung der Überwachung der Systeme im Hoch- und Tiefbau

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SUMMARY
This paper reviews progress on the development of knowledge based systems to assist in the interpretation of signals from instrumentation. The instrumentation concerned is that used to monitor civil engineering structures or systems. Two examples are given. In the first, a signal derived from the non-destructive testing of a pile is characterised in a novel hierarchical way using a pattern grammar. The second uses data from embankment dams, and both rely on stored engineering experience in the interpretation process.

RESUME
Ce rapport présente les progrès dans le developpement de systèmes à base de connaissances pour assister l'interprétation de signaux émis par des instruments. Ces instruments sont ceux utilisés en génie civil pour surveiller des structures ou des systèmes. Deux exemples sont donnés. Dans le premier cas, le signal obtenu par l'examen non-destructif d'une fondation est classifié en utilisant un «pattern grammer» (une grammaire de modèles) sous forme de hiérarchie originale. Le deuxième utilise les informations recueillies de barrages. L'interpretation de chaque exemple est basée sur l'accumulation de connaissances techniques.

ZUSAMMENFASSUNG
Dieses Referat behandelt den Fortschritt in der Entwicklung der wissensbasierten Systeme bei der Auswertung von Signalen der Instrumentierung zur Überwachung von Strukturen oder Systemen im Hoch - und Tiefbau. Zwei Beispiele werden gegeben. Beim ersten wird ein Signal einer zerstörungsfreien Prüfung eines Pfahles hergeleitet, das auf eine neue hierarchische Weise durch Verwendung eines «Pattern grammar» charakterisiert wird, das zweite verwendet Daten von Dämmen. Beide verwenden für den Auswertungsprozess gespeicherte technische Erfahrung.

1. INTRODUCTION

The term "monitoring" when used in the civil engineering context can be applied to a wide variety of situations in which the "performance" of the thing under consideration is being examined. The term is meant to include the use of instrumentation, site investigation techniques and visual inspection.

Monitoring is carried out for two main reasons; to provide an assessment of the performance of an existing structure - feedback, and to provide information for future designs - feed forward. In both cases, as well as providing immediate information on the state of the system , the data provided is of vital importance to the validation of physical and theoretical models. The different types of monitoring often take place over different time scales. The feedforward type of monitoring, used for research as well as design purposes, tends to be more short term, while the feedback performance type of monitoring is usually long term or even permanent. There are exceptions to this generalisation of course. In one of the examples given in this paper, a short term non-destructive test is used to assess the integrity of a concrete pile.

The term performance is used here in its widest sense and is meant to include the safety and integrity of passive structures as well as the operating performance of for example water distribution or hydro-electric systems.

In most fields of civil engineering, monitoring is becoming more widespread. This is partly because of the need to maximise the economic performance of a system, partly because of increasing public demand for a "safe" environment, and also because the technology has advanced to a point where the required monitoring is both economically and technically realistic. However, although the instruments and associated computerised data acquisition have advanced considerably, the interpretation process has changed only a little. It is this area which needs attention.

One of the main difficulties hindering the effective use of monitoring is the management of the data produced.So much data is being, or can be, produced , and it is of such complexity and variety that it can become too much to handle [1],[2] . In such cases the data is filed away and never used. The purpose of this paper is to suggest aids in the process of data interpretation which will help in the overall management of the monitoring information.

2. CHARACTERISTICS OF CIVIL ENGINEERING DATA

The nature of the data collected from civil engineering monitoring is that it is peculiarly uncertain.The uncertainties arise in the way the data is collected,the types of systems being considered,the types of materials used and the methods of construction employed. Measurements taken are usually samples of parameters varying continuously in space and time. The measurements are often sparse in space, and may be irregular in time, requiring careful correlation and interpolation.The instruments used in the measuring process are often not measuring directly the desired parameter. For instance, to find stresses we often measure strains and then rely on an uncertain knowledge about prototype material properties. Also in a complex structure the desired parameter may be obscured by a more energetic effect. For example, in the case of the non-destructive pile test described below, the interpreter has to distinguish the signal due to internal sound waves from that due to surface waves when the pile is struck with a hammer. Other factors such as final instrument position or orientation add to the uncertainties.

Physical measurements form only a part of the monitoring process.A further ,and most important part includes visual observations and verbal descriptions of the current state of the system.These factors taken together make the use of conventional signal and data processing techniques of limited use.

3. INTERPRETATION

The sound interpretation of data requires a detailed knowledge of system being considered, and the types of instruments and data recording methods being used and must be based on proven engineering judgement and experience. The expert interpreter will also use background heuristic knowledge about past and present site conditions, the contractors involved in construction and a myriad of other odd bits of information. However, this is not always enough, even though he may have both "shallow" and "deep" knowledge about the systems, the human interpreter is limited by his ability to hold sufficient spatial and temporal correlations in his mind at one time.This can be illustrated by looking at the case of an embankment dam. Well instrumented dams may have several hundred instruments installed to produce a sparse spatial sampling of a number of parameters. A good dam engineer may be able to infer that certain events are happening because of a few particular signal characteristics. He can isolate parts of signals which have sudden changes, or which have flatter patches than expected, or he may detect such things as global drifts. He would certainly apply windowing in his analysis. However, pulling together all the little bits of evidence to provide an overview of the health of the dam is both very difficult and time consuming. A remarkable amount of dependable correlation does occur, but the engineer may be unable to explain his "hunches". This is a serious limitation when important safety decisions are being made.

It is interesting to note that the experienced engineer can form judgements based on the shape of the signal alone without reference to the numerical values. The shapes displayed to him are compared with models held in his mind, some of which are from a picture library assembled from previous experience, while others are made up at the time based on an understanding of the physics of the system.

Knowledge based systems can help in the interpretation process by;

(1) Compressing, handling and storing large amounts of data intelligently.

(2) Isolating important information

(3) Using the computers concentration and memory capacity to explore the data to infer relationships and highlight peculiarities

(4) Bringing together instrumentation data with qualitative data and stored background knowledge to provide inferences which can be explained.

Conventional methods of signal processing can help with the second of these points, but there are only a limited number of types of transformations which can be used and many of these are inappropriate for the sort of data usually found in the civil engineering context.

The third point can only be effectively tackled if there is a convenient means of representing the data in a form suitable for interfacing with the knowledge base.

In order to overcome both these difficulties a hierarchical method of presenting signal data has been developed which enables linguistic descriptions of the features of the data to be made.

4. HIERARCHICAL SIGNAL MANAGEMENT

The aims of the hierarchical signal management are two-fold. Firstly to present an intelligent compression of the raw data signal and secondly to present the compressed data in a form which can be readily manipulated by a knowledge base.

The first aim is achieved using vectors to represent segments of the signal, the second aim is achieved by describing strings of vectors in words .The words are then be assembled into formal structures for recognising features known as pattern grammars.

The processes described below were developed to assist in the interpretation of the signals produced in the in-situ testing of concrete piles[3] . The signals came from a geophone attached to the cap of a concrete pile after the head of the pile had been struck., figure 1.The figures used to illustrate the process refer to this situation.

4.1 Data Compression

The importance of signal shape has already been mentioned and these ideas are embodied in the methods described here. The signal is modelled both in terms of its shape, represented as a series of vectors, and its value represented as a series of steps. However only the hierarchical representation of shape will be considered in this paper.

The signal is first divided into sections of previously specified length. These sections are then classified as belonging to one of a number of limited classes of vectors. Figure 2 shows the vector space divided up into five classes. The vectors have the same length so that initially each section of the signal is specified solely by its shape class. A sensitivity factor is used to control the deviation of the vector representation from the original signal. If the deviation is too great the length of the vector is changed. This gives a two number code for each section of signal; class and length. The signal can then be portrayed either graphically or by a string of code numbers (figures 3, 4).

If there are any successive vectors of the same class these are concatenated and then the lengths are further classified so that the signal is eventually represented as a string of two digit codes.

The level of representation in the hierarchy is thus controlled by five parameters chosen by the user. They are (1) the initial length of the vector, (ii) the initial signed section length, (iii) the number of vector classes, (iv) the sensitivity factor and (v) the resolution of the final length classification. The resulting codes can then be operated on directly or output to a pattern directed inference system (PDIS), as in figure 3.

4.2 Pattern Grammars

Syntactic pattern recognition techniques have been used previously in such areas as medical electronics [4]. The idea is that an expert may be able to recognise complex features in a signal as being significant. If he is able to verbalise descriptions of these features they can be broken down into pattern primitives or basic shapes. The way these basic shapes are combined together to form higher level patterns is known as the pattern grammar. The grammar is specific to any particular recognition task.

In the case reported here the basic forms or pattern primitives are made up from various sequences of vector codes. An example is shown in figure 5.

The two processes described above enable representation of the shape of signals at multiple levels of detail. The level of detail chosen is that appropriate to the problem at hand. These processes can be viewed as changing the language of the signal from binary data to linguistic descriptions which are compatible with qualitative data and engineering knowledge contained in a KBS

5. INTERFACING WITH KNOWLEDGE BASED SYSTEMS

The other project mentioned earlier deals with the case of an embankment dam where there are many signals being recorded from a wide variety of sources rather than the one very confused signal given in the example above [5]. The work on this second project has considered a different way of characterising the time series data from the dam.

Although the pattern recognition techniques described in the example above are applicable to a certain extent in this second case, the expert is trying to detect patterns which represent deviations from norms rather than ones which will fall into predetermined classes. It is important in this kind of situation to avoid the trap of only looking for known faults, the system must be able to isolate conditions of which it has no experience.

A pilot system has been constructed using a numerical simulation of a zoned dam as the "input" with signals coming from eight piezometers in the core of the dam recording changes due to a fluctuating reservoir level. Figure 6 shows the arrangement of the instruments with typical signals. In this first stage, the signals were characterised using three global statistical measures of their behaviour. These were standard deviation, "uniformity" which gave an indication of discontinuities and "extremeness" which gave an indication of the dwell of the signal at maximum excursions from the mean. These characteristics were chosen after discussion with dam engineers as being most meaningful intuitively when scanning graphs of the data. It also enabled a rapid compression of say 200 data points into 3 characteristics. Two knowledge bases were then constructed using elicited knowledge and numerical simulations. The first knowledge base related the numerical values with the expected rarity of occurrence. Dam engineers were shown graphs of instrument signals and asked to classify them as not rare, moderately rare, very rare high or very rare low. These opinions were cross checked with a large number of runs of a dam simulation into which were injected artificial random errors.

The second knowledge base was used to determine how the rarity values of the individual characteristics should be combined to give an overall level of "cause for concern" for each instrument. It was constructed initially by hand. All the possible combinations were written down and values of cause for concern assigned to them. Later these relations were refined using an automated optimisation scheme operating on a training set of examples.

The resulting levels of cause for concern were applied to each individual instrument. It was considered vital that this information be presented pictorially to make the situation clearer rather than confuse it with yet more data. In this pilot scheme a picture of the cross-section of the dam was displayed with a shading pattern superimposed representing the level of concern at any point figure. The shading at each point was determined using an inverse low interpolation between the instruments.

The system can be interrogated about how it came to its conclusion about the level of concern using the screen cursor. In response, the system displays the concern level and the rarity levels for each of the characteristics of the instruments which dominated the assessment. Figure 7 shows a cause for concern map and a consequent interrogation.

Given the same initial signals experienced dam engineers were unable to come up with as succinct a description of the safety implications and had difficulty explaining the conclusions they did draw.

6. CONCLUSIONS

This paper has illustrated ways in which large amounts of instrumentation signal data can be intelligently compressed, handled and interfaced with knowledge bases for subsequent interpretation.

A pattern recognition type of signal processing system has been developed using a hierarchical vectorisation of the signals. Pattern grammars have been used to successfully describe and recognise features of signals from the non-destructive testing of piles.

A pilot system for the analysis of instrumentation from an embankment dam showed how even a simple characterisation can produce results which are more methodical and sensitive than those produced by a typical engineer.

7. ACKNOWLEDGEMENTS

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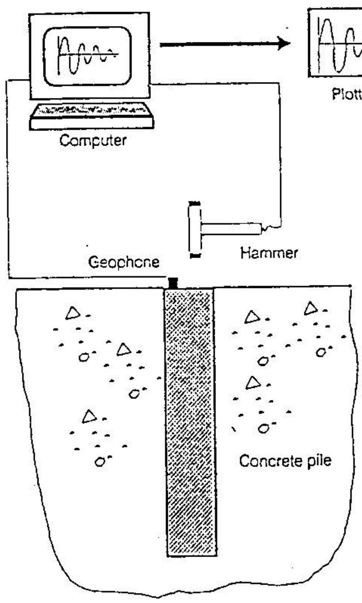


Figure 1 The non-destructive pile testing system.

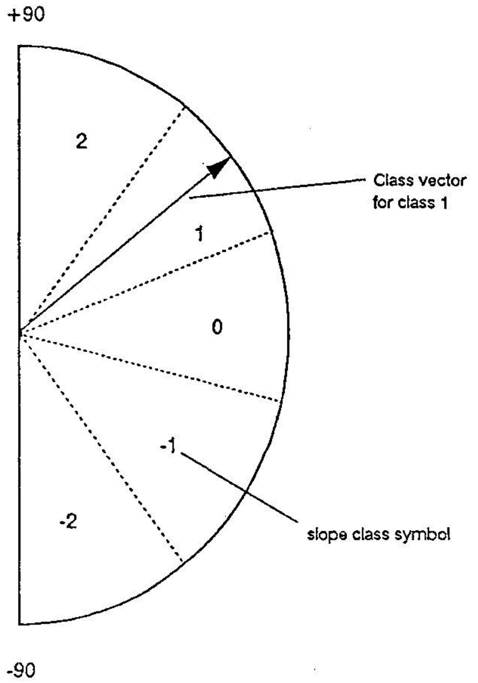


Figure 2 An illustration of the vector space divided into 5 classes.

slope class symbol	length time units
0	6
-2	30
-2	30
-2	30
0	30
1	30
2	30
2	30
1	30
2	30
1	30
-1	30
1	30
1	30
0	30
0	30
0	30
0	13

Initial coding
(a)

slope class symbol	length time units
0	6
-2	90
0	30
1	30
2	60
1	30
2	30
1	30
-1	30
1	60
0	103

Concatenated
(b)

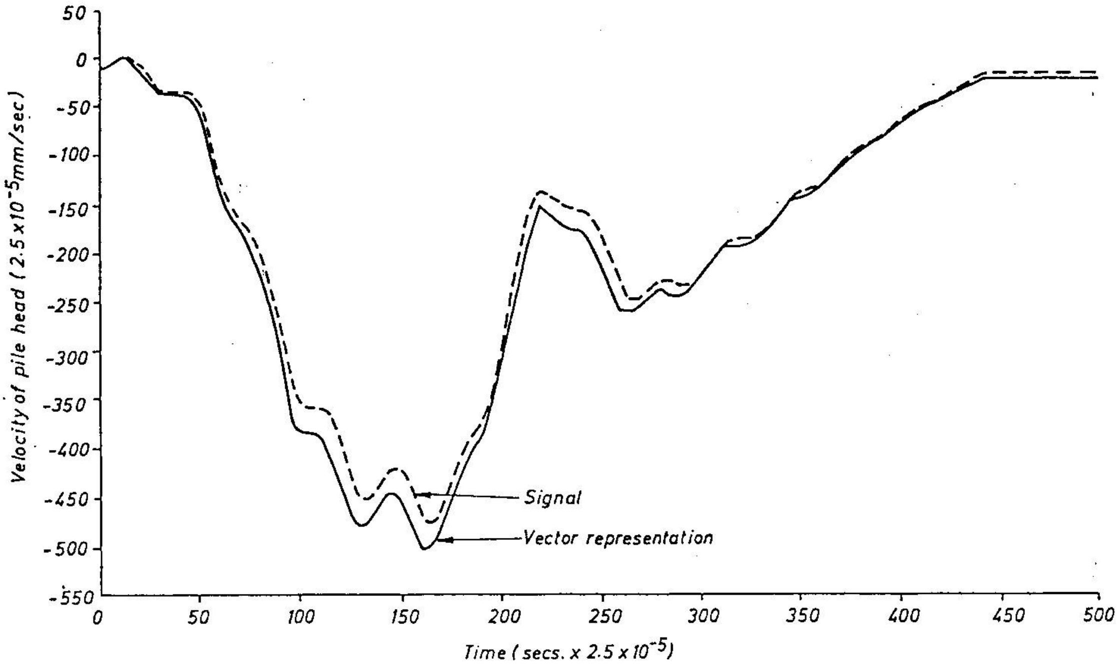
slope class symbol	length class symbol
-2	3
0	1
1	1
2	2
1	1
2	1
1	1
-1	1
1	2
0	3

Lengths quantised
(c)

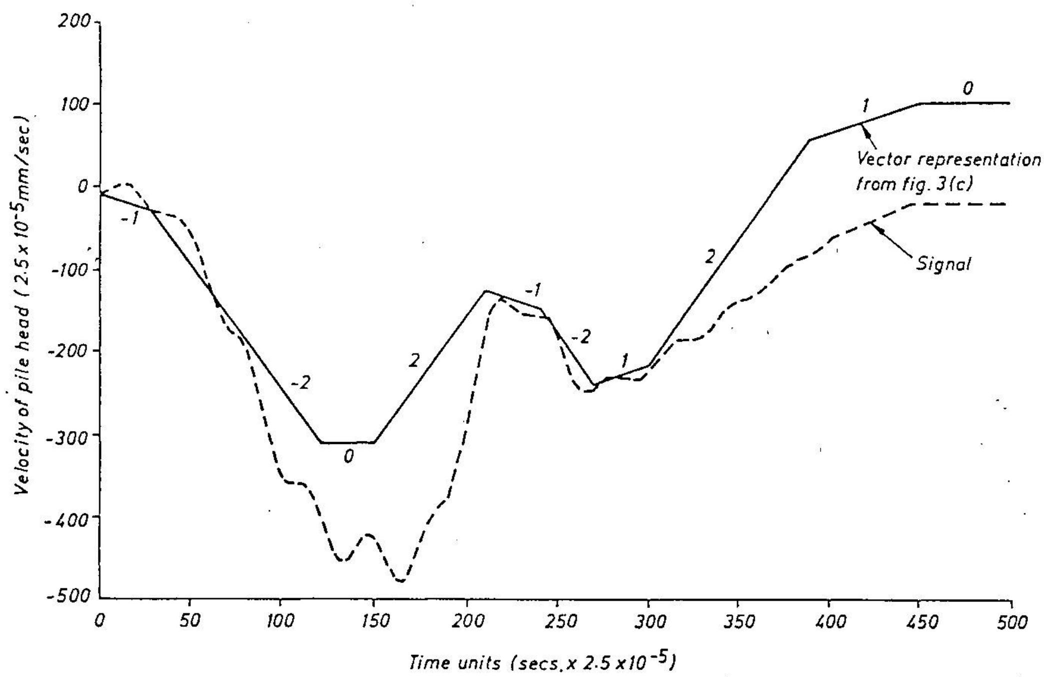
```
pile_med(pile_no,[
        -23,
          1,
         11,    <--- Chain code
         22,
         11,
         21,
         11,
        -11,
         12,
          3 ]).
```

PROLOG predicate
(d)

Figure 3 An example of the characterisation of signal from initial vectorisation to PROLOG predicate.



AN EXAMPLE SIGNAL : SHAPE REPRESENTATION
No. OF VECTOR CLASSES = 51
INITIALLY SPECIFIED LENGTH = 10 TIME UNITS
PRIMITIVE VECTOR LENGTH = 10 TIME UNITS



AN EXAMPLE SIGNAL : SHAPE REPRESENTATION
No. OF VECTOR CLASSES = 5
INITIALLY SPECIFIED LENGTH = 30 TIME UNITS
PRIMITIVE VECTOR LENGTH = 30 TIME UNITS

Figure 4 Representations of signal shapes at two levels in a hierarchy.

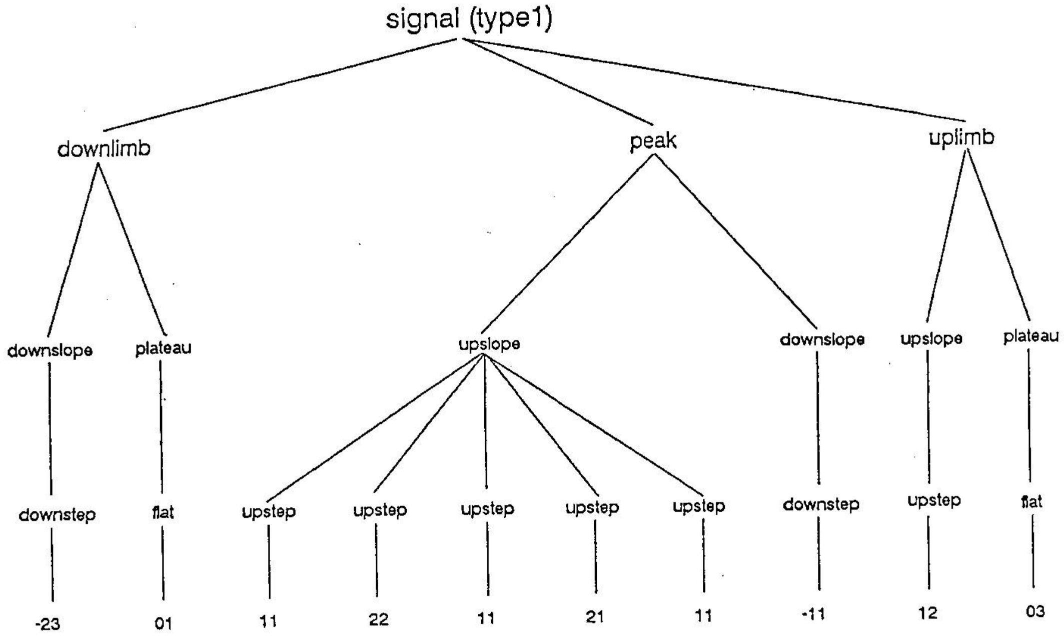


Figure 5 A Parse tree from the pile pattern grammar.

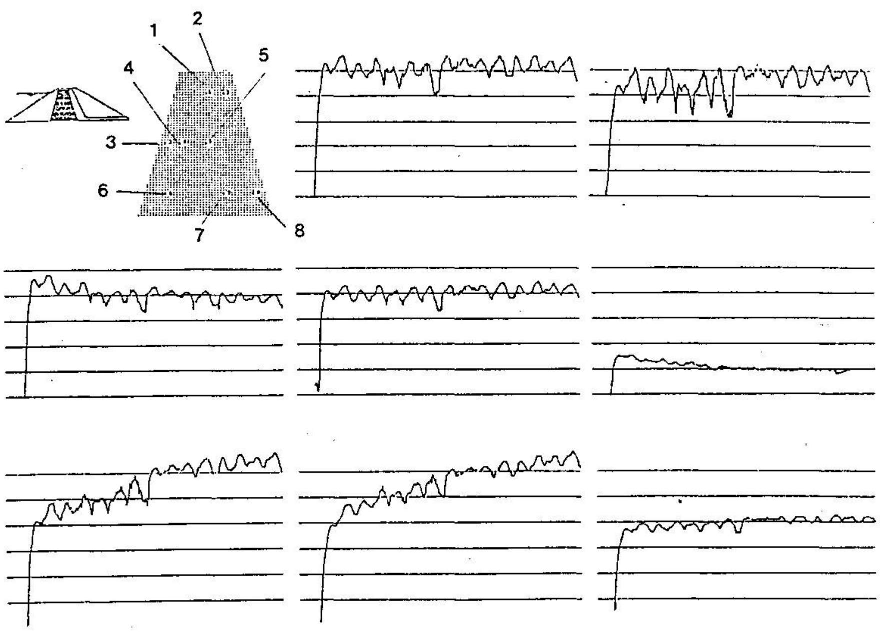
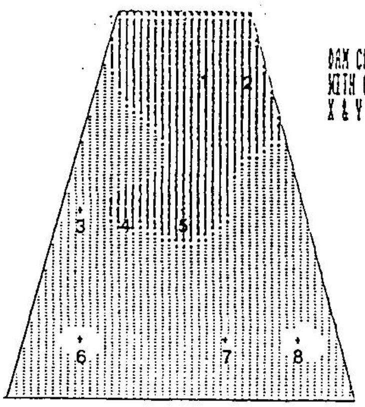


Figure 6 The model dam with typical instrument signals.



DAM CROSS SECTION
WITH CORE DETAIL SHOWING INSTRUMENTS
X & Y of interest?15,22

```
Concern   at X= 15. & Y= 22. is 35.
All insts contribute ( 18.% except
INST No1.giving 13.% of case GMT concern  =18.
INST No4.giving 25.% of case GMX concern  =52.
INST No5.giving 34.% of case GMT concern  =18.
INST No6.giving 15.% of case GØV concern  =84.

MORE ?

>YES

WHICH INSTRUMENT IS OF INTEREST ?

>4

CONCERN GMX COMPRISES


A  TYPICAL  EXTREMENESS RATIO

A  TYPICAL  STANDARD DEVIATION RATIO

A  VERY RARE HIGH  UNIFORMITY RATIO

MORE ?

>NO

CONSULTATION ENDED
```

Figure 7 Typical output with an interrogation.