PATTERN RECOGNITION FOR REMOTE SENSING:

Progress & Prospects

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ABSTRACT

An overview is presented of the current state of automatic image pattern recognition as applied to remote sensing of the earth's resources. The framework for the discussion is four key aspects of the remote sensing problem: scene information content, characterization of scene information, information extraction methods, and the net value of extractable information. Outstanding problems and the prospects for future developments are surveyed. The impact of increasingly complex data bases and the rapidly evolving digital computer technology are highlighted.

INTRODUCTION

In the mid-1960s, pattern recognition was introduced as a means of analyzing multispectral image data collected by multispectral remote sensing -- at that time by multispectral scanners aboard aircraft. It was quickly demonstrated that when the ground covers of interest were spectrally discriminable (as many as 15 to 18 spectral measurements could be made on each pixel), pattern recognition provided an automatic means for classifying the data [1]. Automation was deemed essential because of the large volumes of complex data produced by remote sensors. In the years that followed, however, two developments in remote sensing have challenged the pattern recognition enthusiasts to extend the capabilities of this approach:

1. The desirable applications of remote sensing have begun to involve much more subtle distinctions in terms of spectral differences.

2. The principal sensor of interest, the Landsat multispectral scanner (MSS), is relatively limited in spectral range and both spectral and spatial resolution.

The challenge has been well met, however, and recent years have seen the demonstration of important and large-scale earth resources monitoring applications based on pattern recognition analysis of remote sensing data [2,3].

What is the state of the technology now and what are the prospects for future developments? As progress continues to be made in the sister technologies concerned with information systems and digital computers, the potential for developing ever more powerful and useful pattern recognition methods for remote sensing image processing continues to expand. A survey of the frontier follows.

Components of "The Problem"

It is helpful to organize consideration of the overall remote sensing information extraction problem into four major components. We can thereby focus our attention on manageable pieces of the total problem, even though

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it is necessary to keep in mind that the interactions of the components are of major significance in addition to the characteristics of the components themselves.

The components to be considered are as follows:

1. The amount and nature of actual scene information content.
2. Characterization and measurement of available scene information.
3. Information extraction methods.
4. The value of extractable information.

It will be helpful to cast the discussion of these components in terms of a specific application scenario to make the discussion more concrete. "Crop inventory" or "commodity production forecasting" will be the focus because this application problem is well-defined, fairly well understood, moderately complex, and an application to which the author has had considerable exposure.

The Application Scenario

The application problem is to use multispectral remote sensing as a primary source of data for estimating crop production on local, national, and global levels. Other data inputs, collectively referred to as ancillary data, are used to the extent they are available and can improve the production estimates without unduly increasing the cost of obtaining the estimates. Examples include meteorological data, agronomic variables such as soil type, and relevant historical information.

Measures of the quality of a production estimate include its accuracy, precision, and reliability, its timeliness, and the cost of obtaining it.

Crop production can be estimated by means of the following model (due to Dr. Donald A. Holt, Department of Agronomy, Purdue University):

Crop Production = Crop Acreage x "Maximum Yield" x Weather Factor x Episode Factor x Management Factor.

Crop Acreage is the ground area occupied by a viable crop of a given species. "Maximum Yield" reflects the maximum yield potential of the planted area based on climate and agronomic variables influencing soil fertility. The Weather Factor accounts for meteorological deviations from the ideal that would result in Maximum Yield. The Episode Factor accounts for events, such as hail storms, disease or floods, which may have a devastating effect on yield. And the Management Factor reflects the impact of economic and/or technological developments which could influence production. For example, a new variety of a wheat may be found to yield more than the "Maximum Yield;" or a market glut may result in a portion of the crop being plowed under rather than harvested. Crop acreage can be provided, for many crops, by classification of remote sensing data [4]. Remote sensing can also provide some information useful in determining the other factors of crop production.

One possible way of storing and processing the data required for this crop production model is suggested by Figure 1. In Figure 1(a), the various factors are shown as "maps" which could be stored as digital grip maps. Such maps then become layers in a data base, Figure 1(b), from which the production for each crop of interest may be systematically extracted.

In practice, it would probably not be efficient to store all of the relevant factors as grid maps, but, in any case, the data base formulation would maintain the spatial correspondence, or "registration," among whatever forms of storage were utilized. It is convenient to visualize the data base as shown in Figure 1(b).

Now we return to the four major problem components introduced earlier and examine the state of the technology relative to each.

SCENE INFORMATION CONTENT

Given all feasible sources of data about a scene of interest, how much information about the scene is actually contained in the data?

Electromagnetic sensors, passive and active, are the principal data sources considered in remote sensing, but there are many other possibilities extending even to ground observations and historical data, for example. The various sources have differing degrees of resolution, accuracy, precision, and reliability. In terms of the application scenario, even though the remote sensing data is collected on a (relatively) uniform and high resolution grid, this will certainly not be the case for related soil maps, topographic maps, and meteorological data.

Ideally, it would be desirable to be able to measure the total amount of information about a scene contained in all available data components. This is bound to remain an elusive ideal, however. For one thing, "information in the Shannon (signal representation) sense," for which various quantitative characterizations are known, is scarcely relevant when the data analysis objective is classification. Effective measures of information which are based on discriminability of classes of interest, necessarily depending on the identity of those classes, have not yet been established, although some good progress has been made [5,6].

Good laboratory work can determine to a considerable extent how much information is available under idealized conditions, and this is an essential ingredient in every aspect of practical remote sensing, from sensor design to mission planning to data analysis. The "laboratory" may be test plots on an experimental farm, typical forested or urban settings, etc., and the "laboratory" instruments may be bench-mounted, vehicle-mounted or even airborne. The point is that data gathered under carefully controlled and well-documented circumstances can be of great value in demonstrating the best that can be done with remote sensing. Fortunately, the value of this approach is being more widely recognized and supported [7]. But more basic work needs to be done to better model the effects of corrupting factors such as atmospheric and sensor noise and the effects of geometric registration errors.

INFORMATION MEASUREMENT AND REPRESENTATION

For a specified data base and an associated application, what are the characteristics or "features" of a scene that, through appropriate processing, may be expected to yield the desired information? Again referring to the application scenario, the spectral measurements on each pixel may not be adequate to discriminate among important crops, much less crop or environment conditions which may substantially impact their yield. Spatial and temporal variations in the scene can carry essential information as can topographic data in areas exhibiting significant variation of elevation. The "raw" data, assumed here to be spectral measurements of the scene, convey relatively rudimentary information about the scene if considered only a pixel ("picture element") at-a-time.

As noted earlier, when the multispectral scanner became available for civilian remote sensing applications during the 1960s, the machine processing and pattern recognition research focused at first on the pixel-by-pixel spectral measurements. The spatial characteristics of the data were largely ignored because it was not known at that time how to represent them in the computer and the dimensionality of the data was already in excess of what could be dealt with using the available computer technology.

While the earth resources part of the remote sensing community was working on automatic extraction of spectral information, the military community was concentrating on automation of spatial analysis, more closely allied to the traditional military use of manual photointerpretation. More recently we have begun to see each of the two camps drawing on lessons learned by the other; spatial and spectral features are beginning to be used jointly in the analysis process. Significant progress in the characterization of texture, shape, and structural relationships is appearing in the image processing literature. While this facilitates the representation of such features in the machine, relatively little progress has been made in incorporating the features into the analysis process, i.e., learning how they distinctively characterize classes of interest.

Temporal scene variation has long been hypothesized as having great potential as a source of discriminatory information. Availability of periodic observations from Landsat has provided the opportunity to test this hypothesis, once the capability was developed to adequately register data from temporally separated passes of the satellite [8]. The most direct approach to analyzing multitemporal data is to create "stacked" data vectors by simply concatenating sets of measurements from successive observations of the site. The same analysis methods applied to unitemporal data may then be applied to the multitemporal data. This raises a number of issues, however. First, it is not yet known with any generality how sensitive the analysis methods are to the inevitable registration errors, which may range from a fraction of a pixel to several pixels, depending on characteristics of the remote sensing data and the methods selected for performing the registration. The effects are certainly significant in highly variable regions and at object boundaries in the data.

Second, the substantial increase in the dimensionality of the analysis task raises the complexity and the cost of the analysis and may even require the application of dimensionality reduction methods. A number of interesting methods for dimensionality reduction have appeared in the recent literature but have yet to be tested [6].

And finally, there is evidence suggesting that simple "measurement space" features are not the most information-bearing characteristics of multitemporal data. It has been found, for example, that temporal trajectories of "greenness" and "brightness" features are better for discriminating among some crop species [9]. This is certainly not surprising and it reinforces the notion that important information about earth resources may yet be obtainable from remote sensing data through the investigation of rather complex transformations of the raw sensor data.

INFORMATION EXTRACTION

Once the information-bearing features are known, what techniques are necessary to extract effectively the needed information? Given the characteristics of the data base and the application, how can the class of admissible (potentially useful) information extraction procedures be described? Of the admissible procedures, which are feasible in the context of existing technology? Of the feasible procedures, which of these may be optimal from both cost and performance viewpoints? What cost/performance tradeoffs must be accommodated?

For more than a decade, statistical pattern recognition techniques have been applied to remote sensing data on a pixel-by-pixel basis. The procedures incorporating this approach have become increasingly sophisticated, with particular attention being given to assisting the data analyst in developing a valid characterization of the multivariate measurement space based on "ground truth" which, for reasons of economy, is as limited in extent as possible [10]. Implementations of the basic statistical decision process have also become increasingly sophisticated, primarily in order to increase the speed of processing and enable larger data sets to be processed in as timely and economical a fashion as possible. Examples of such implementations include table-lookup methods for general-purpose computers and the use of parallel processing systems, such as ILLIAC IV [11] and STARAN [12], and array processors which can be appended to general-purpose host computers [13].

Aside from the texture and temporal features mentioned in the previous section, which generally have been used in addition to or in place of the basic spectral features, until recently very little progress has been observed toward utilizing other information-rich features of the remotely-sensed scene. Spatial information in the remote sensing data and numerous other forms of information available from digitized maps, etc., have been utilized in manual interpretation of the data, but new approaches to image pattern recognition have not been available to enable the computer to make effective use of such information sources.

The basic maximum-likelihood decision rule has now been extended to apply to classification of multi-pixel "objects" [14], i.e., regions with relatively homogeneous spatial and spectral features. The objects may be located by manual means or by automated scene segmentation techniques. When the objects are large compared to the resolution of the sensor and the segmentation procedure is effective, the object classifier greatly speeds the processing and improves the accuracy of the results. This approach has not been widely applied to Landsat data because the resolution of the Landsat multispectral scanner is not sufficient to result in large objects. However, satellite sensors under construction, both scanners and linear array ("pushbroom") devices and also aircraft-borne sensors will produce data of sufficient resolution to warrant the segmentation/object classification approach.

The Bayesian decision strategy for classification can be extended in a different fashion to incorporate neighborhood information about a pixel to be classified [15,16]. Taking this approach, a neighborhood of fixed size and shape is defined. A probability distribution characterizing the likelihood of observing all possible contexts (neighboring class configurations) is used together with the usual class-conditional probabilities to classify each pixel. It has been demonstrated that this classifier model can be quite effective in improving classifier accuracy provided the context distribution can be adequately estimated. (Numerous methods for performing this estimation are proposed.)

In terms of the application scenario, both of the foregoing methods for classification using contextual information have been shown quite effective for improving the accuracy of classification.

Still more general spatial relationships can be utilized through application of syntactic methods for pattern recognition and image analysis [17,18]. The approach is to develop "pattern grammars" analogous to the grammars used to describe natural languages or programming languages. The grammars aid in assessing the "meaning" of an image based on the structural relationships among pattern primitives. Thus, for example, roads may be described and recognized as strings of pixels classified as "blacktop" or "concrete"; lakes may be discriminated from rivers based on structural relations of "water" pixels, and so on. While some interesting results have appeared based on this approach, much research remains to be done before syntactic image analysis will be widely applicable in practice.

The useful context related to applications of remote sensing data is not limited to the remotely sensed image alone. Ancillary data may be used in conjunction with remote sensing data, either as part of the pattern recognition operations based on the remote sensing data or in subsequent post-processing steps. For example, topographic variables have been used to significantly improve the extraction of forestry resources information from Landsat data [19]. The application scenario sketched earlier in this paper represents another potential application of this general concept which remains to be exploited. It may be argued (and will be) that the development of general and effective techniques which provide for the coordination and joint analysis of multiple data sources and types represents one of the most important areas for remote sensing data processing and analysis for the foreseeable future.

INFORMATION UTILIZATION

Is the extractable information of sufficient value so that someone is willing to pay the cost of obtaining it?

There are a number of important issues embedded in this question. First, what can be done to minimize the cost of obtaining the information? Cost might be reduced at many different stages, from data acquisition through preprocessing and on to information extraction.

What can be done to maximize the value of the information to the consumer? Improved accuracy and reliability obviously enhance the value of the information, as does timeliness for most applications. Users need the results available in a convenient form, often a form which permits reformatting or resummarization for multiple uses.

Together with the commitment, recently taken by the U.S. government, to provide multispectral remote sensing date on an operational basis, there is an urgent need to assess what form that data should take. Widespread use of the data stands to considerably reduce its cost. But obtaining such use may entail substantial initial investment in development to provide "universally" useful data. The sensor systems must be capable of providing data virtually on command and with spatial and spectral characteristics well suited to the application(s) at hand.

Happily the computer and information systems technologies are evolving rapidly in directions which promise to reduce the cost and improve the timeliness with which information can be extracted from remote sensing data. As computers and memory devices are becoming faster and larger, the cost of processing power and memory are continuing to drop. It is becoming realistic to think of having very large and complex data bases on line for processing. Now, how can they be used most effectively?

WHERE TO FROM HERE?

Which brings us to the final point of this paper, namely, directions for the future. As already suggested, remote sensing data is going to prove most useful when it serves as one or more components of a multifaceted data base and information system. Methods for effectively analyzing the data in such a complex environment do not yet exist. The methods which have been developed for analyzing only remote sensing data are not trivially extendable to meet this need.

Figure 2 casts the problem again in terms of the application scenario involving crop production forecasting. The data analysis methodology implied by the righthand side of the figure might well be expected to have the following characteristics:

1. The data base can be addressed at any time to produce an information update based on the currently resident data.

2. The data types contained in the data will be considered on a weighted basis, the weighting factors based on a measure of "marginal information content" and the estimated reliability of each available data attribute.

3. The information extraction capability will suffer, at worst, "graceful degradation" in the face of missing or unreliable data.

4. The results of any information extraction process will always include a measure of the quality of the information produced. Accuracy, precision, reliability and timeliness are pertinent in deriving such a quality measure.

It is possible to conceive of a generalized hierarchical form of discriminant analysis applicable to such a situation, but the details of such an approach are still very much topics for research.

REFERENCES

1. K. S. Fu, D. A. Landgrebe and T. L. Phillips, "Information Processing of Remotely Sensed Agricultural Data," Proc. IEEE, Vol. 57, pp. 639-653, April 1969.

2. K. R. Boiko, "St. Regis, NASA Join Forces in Timber Project," Paper Trade Journal, May 16-31, 1978.

3. R. B. MacDonald and F. G. Hall, "LACIE: An Experiment in Global Crop Forecasting," Proc. Plenary Session of the LACIE Symposium, pp. 17-48, NASA/Johnson Space Center, Houston, TX, October 1978.

4. M. E. Bauer, J. E. Cipra, P. E. Anuta and J. B. Etheridge, "Identification and Area Estimation of Agricultural Crops by Computer Classification of Landsat MSS Data," Remote Sensing of Environment, Vol. 8, pp. 77-92, 1979.

5. B. F. Merembeck and B. J. Turner, "Directed Canonical Analysis and the Performance of Classifiers Under Its Associated Linear Transformations," Proc. Symp. Machine Processing of Remotely Sensed Data, Purdue University, IEEE Cat. No. 79CH1430-8 MPRSD, pp. 314-322, 1979.

6. H. P. Decell, Jr., and L. F. Guseman, Jr., "Linear Feature Selection With Applications," Pattern Recognition, Vol. 11, No. 1, pp. 55-63, 1979.

7. M. E. Bauer, M. C. McEwen, W. A. Malila and J. C. Harlan, "Design, Implementation and Results of LACIE Field Research," Proc. LACIE Symposium, Vol. II, pp. 1037-1061, NASA/Johnson Space Center, Houston, TX, Oct. 1978.

8. D. K. Barnea and H. F. Silverman, "A Class of Algorithms for Fast Digital Image Registration," IEEE Trans. Computers, Vol. C-21, pp. 179-186, February 1972.

9. P. N. Misra and S. G. Wheeler, "Crop Classification With Landsat Multispectral Scanner Data," Pattern Recognition, Vol. 10, No. 1, pp. 1-13, 1978.

10. D. Scholz, N. Fuhs, M. Hixson and T. Akiyama, "Evaluation of Several Schemes for Classification of Remotely Sensed Data: Their Parameters and Performance," Proc. Thirteenth International Symp. on Remote Sensing of Environment, pp. 1143-1149, Environmental Research Institute of Michigan, Ann Arbor, MI, April 1979.

11. G. Hanuschak et al, "Crop Area Estimates From Landsat: Transition From Research and Development to Timely Results," Proc. Symp. Machine Processing of Remotely Sensed Data, Purdue University, IEEE Cat. No. 79CH1430-8 MPRSD, pp. 86-96, 1979.

12. S. Ruben et al, "Application of a Parallel Processing Computer in LACIE," Proc. 1976 Int. Conf. on Parallel Processing, IEEE Cat. No. 76CH1127-OC, pp. 24-32, August 1976.

13. ESL, Incorporated, "Advanced Scientific Array Processor," descriptive manual, ESL, Java Drive, Sunnyvale, California.

14. R. L. Kettig and D. A. Landgrebe, "Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects," IEEE Trans. Geoscience Electronics, Vol. GE-14, pp. 19-26, January 1976.

15. P. H. Swain, S. B. Vardeman and J. C. Tilton, "Contextual Classification of Multispectral Image Data," LARS Technical Report 011080, Laboratory for Applications of Remote Sensing (LARS), Purdue University, West Lafayette, IN 47907, January 1980.

16. P. H. Swain, H. J. Siegel and B. W. Smith, "Contextual Classification of Multispectral Remote Sensing Data Using a Multiprocessor System," IEEE Trans. Geoscience Electronics, Vol. GE-17, April 1980.

17. R. C. Gonzalez and M. G. Thomason, Syntactic Pattern Recognition: An Introduction, Addison-Wesley, Reading, Massachusetts, 1978.

18. K. S. Fu, Syntactic Pattern Recognition, Applications, Springer-Verlag, Heidelberg, 1977.

19. M. D. Fleming and R. M. Hoffer, "Machine Processing of Landsat MSS Data and DMA Topographic Data for Forest Cover Type Mapping," Proc. Symp. Machine Processing of Remotely Sensed Data, Purdue University, IEEE Cat. No. 79CH1430-8 MPRSD, pp. 377-390, 1979.

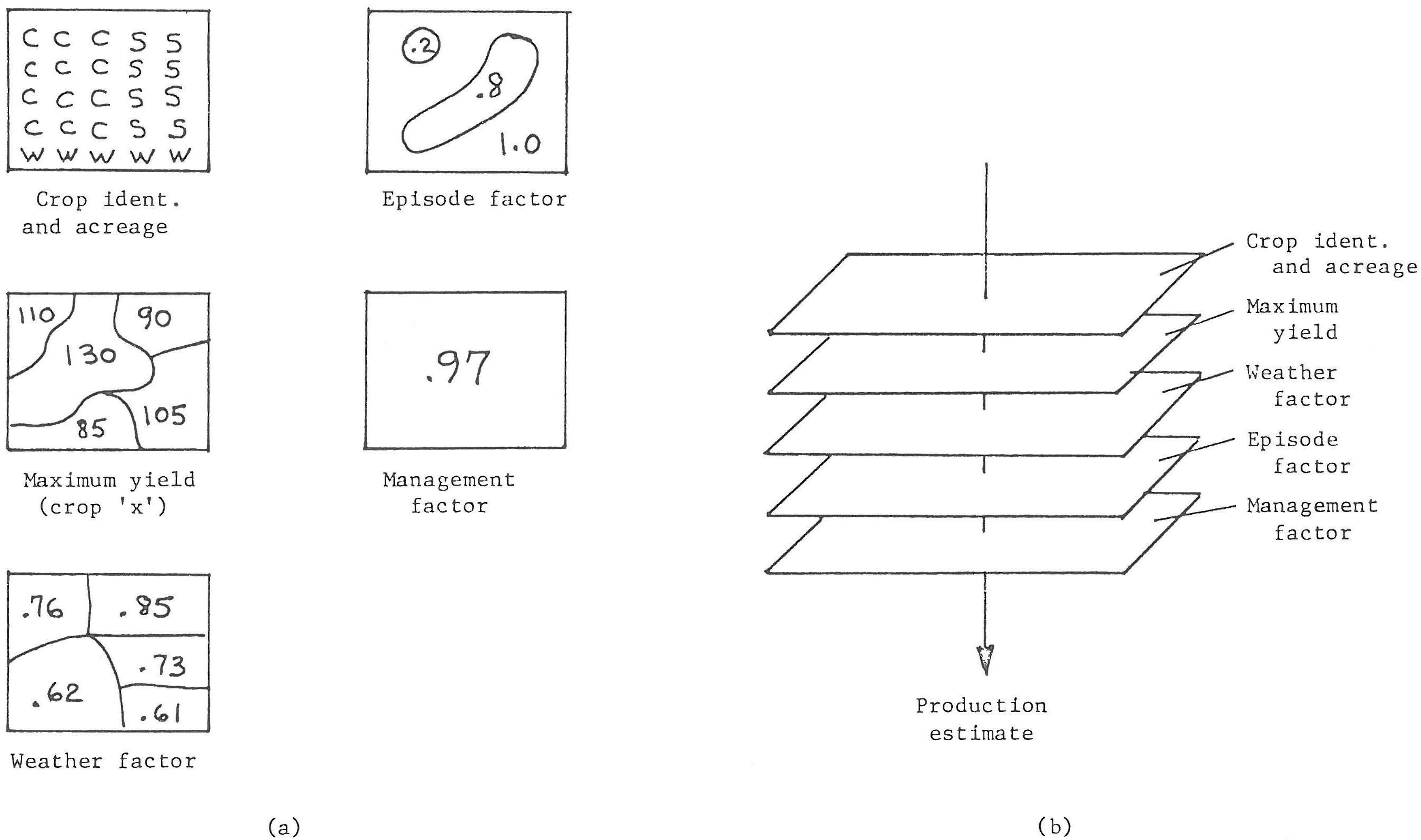

Figure 1. A Data Base for Crop Production Forecasting. (a) Data components (b) Data base and information extraction concept

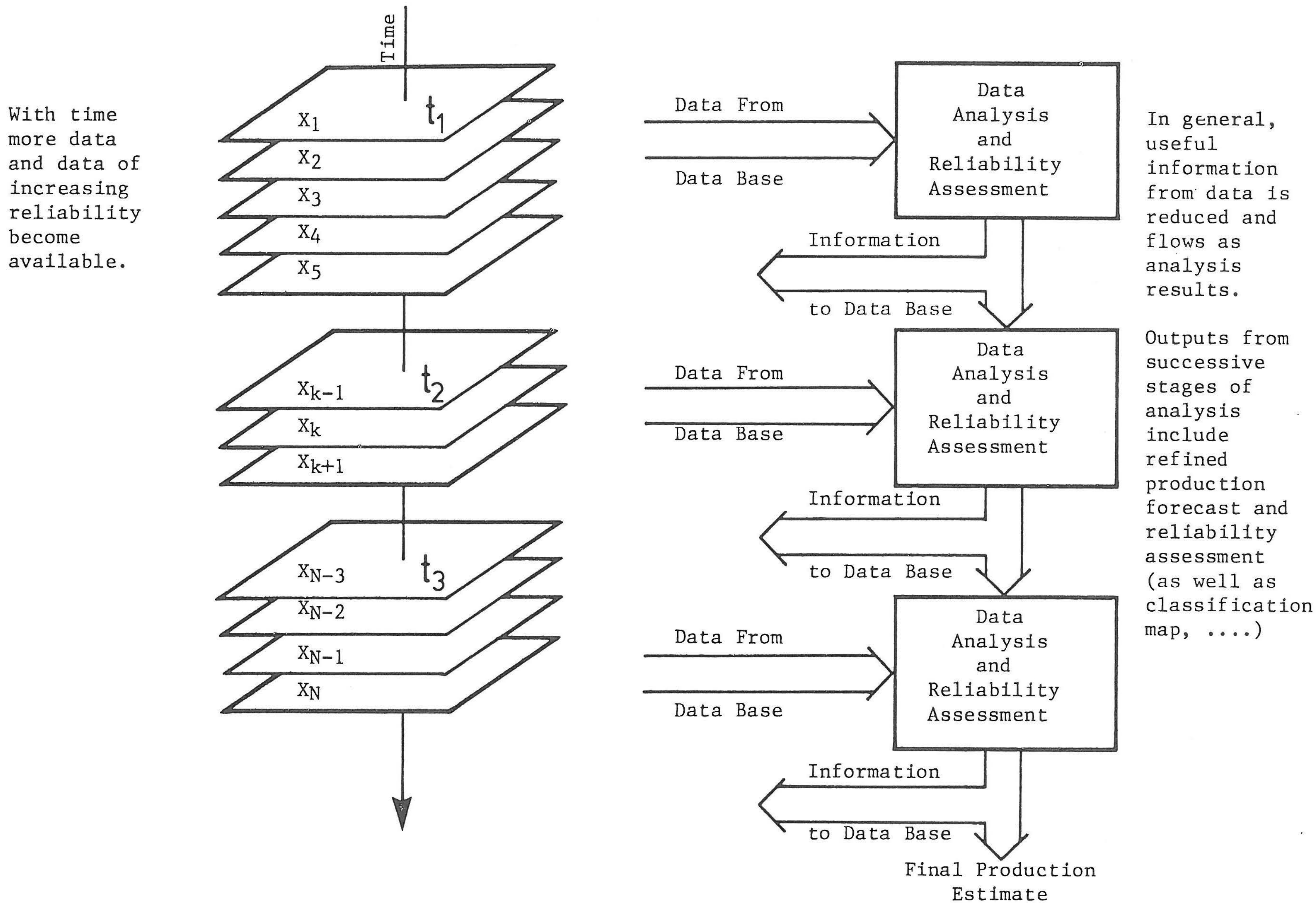

Figure 2. A Hierarchical Information System: General Concept.