Structural class representation and pattern recognition by ETS; a commentary*

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Abstract

Representation of objects and classes is a key issue of pattern recognition research. Traditionally this mainly involved a statistical approach based on the use of features for building vector spaces and the estimation of densities and classifiers. Structural object descriptions have received less attention, mainly as they demand more specific knowledge of the application area and are less suitable for learning pattern classifiers from examples.

The Evolving Transformation System (ETS) aims at a structural description of objects and classes and is entirely different from all previous approaches to pattern recognition. In this paper a discussion is presented on these differences, the possibilities offered by ETS and the difficulties that still have to be encountered. In particular the special definition of the class concept used in the presentation of the ETS will be emphasized. It is based on the natural formative history of objects. This points to applications in which such knowledge exists and may be exploited, like the natural sciences, e.g. genetic structures. ETS might be less suitable for traditional areas like document analysis and image database retrieval if the class concepts are defined late in the development of the system. Like in other structural approaches, the automatic training of classifiers using a set of examples is not easily solved. ETS, however, offers a fundamental and natural approach to pattern recognition. Once it is founded appropriately, it is expected that problems like the formulation of training algorithms can be solved.

1. Introduction

Pattern recognition studies ways to discover pattern classes in sets of objects in the observable world such that newly observed objects can be classified into such classes. This implies a generalization from sets of individual objects into class descriptions that can be applied to new, different objects. Classes may be detected as naturally distinguishable groups of objects, or may be given (but not described or defined) by an expert on the basis of knowledge in a particular area of observations. These two branches of pattern recognition, studying the unsupervised and the supervised problem, have been extensively researched over the past 40 years [1]-[13]. The main approaches fall apart in two different research areas called statistical pattern recognition and structural pattern recognition. In this paper we will comment on a fundamentally new pro-

**In October 2006 Lev Goldfarb tried to constitute a special issue or other collection of papers on the ETS system he has been working on for so long. Unfortunately the project never finished. This contribution remained thereby unpublished.*

posal made by Goldfarb and colleagues that has gradually been developed over the past 20 years [16]-[20]. It belongs to the area of structural pattern recognition, but is still very different from what has been studied so far.

In order to sketch the position of Goldfarb's approach we need first to give a rough characterization of the areas of statistical and structural pattern recognition. In the statistical approach simple representations of objects are used, usually based on a vector space built by features [10], [13] and sometimes by kernels [27] or dissimilarities [29]. Classes are defined in such spaces by analyzing sets of examples (training sets) using statistical arguments: probabilities and densities. It is thereby essential that a training set represents the classes to be separated in a statistical way: it should be possible to estimate probabilities that hold for the future objects to be classified on the basis of the available training examples. Very often this is realized by assuming that the training set is sampled i.i.d. from the same, fixed distribution as the future objects are. Note that this implies that several, possibly almost identical examples should be available in the training set for probable objects with a high density. Improbable objects should be represented with a low frequency, even if they are of special interest, e.g. showing some special characteristics. This is very different from a teacher or a parent that wants to show a child the difference between some groups of objects, e.g. handwritten letters. He will give a single, prototypical example of the class and in addition may show several examples of the borderline cases.

In the statistical approach prior knowledge of the problem may be used in the formulation of features or dissimilarity measures, in the class definitions (the class labels that are chosen) and in the choice of the generalization method: the classifier or the statistical model. This last choice is often difficult as particular distribution is usually unknown in advance. In the case of Bayesian inference such a family is characterized by an assumed distribution over its parameters [8]. It is often difficult within the statistical approach to formulate the available problem knowledge in the probabilistic framework that is offered. Its power, on the other hand is, that once a sufficient general and proper probabilistic problem formulation is found, the lack of knowledge, or the impossibility to formulate it explicitly, can be compensated by learning from (many) examples. Given a sufficient amount of examples the parameters of a flexible model can be estimated in a reliable way, which ensures that the model describes the (training) data well.

In structural pattern recognition objects are more extensively described and, e.g. represented by strings, (stochastic) grammars, or attributed graphs. One mainly focusses on proper encoding of the internal organization of objects, whose structural descriptions are later related and compared often by the use of convenient proximity measures. General procedures to learn from examples are much more difficult than in the statistical approach. More emphasis is put on ways to express available knowledge properly.There is less room to fill gaps in the knowledge by learning from examples.

Several proposals are studied to make use of the rich toolbox of statistical pattern recognition for the rich representations studied in structural pattern recognition [30]. Representations based on kernels [27] and dissimilarities [29] allow for a pairwise numeric comparison of non-numerical objects like text files and protein structures. It is thereby possible to use statistical inference for learning about structurally represented objects. But in that way we learn from the statistics and not from structure itself. The area of structural inference, in the sense of gaining knowledge from the structure in the observations, is almost non-existing [31]. It seems, however, very likely that human beings learn from observing and comparing object structures. For instance, if we want to learn about trees and their types, we study the shapes and structures of their crowns, branches and leaves. We have an opinion about significant differences in the structural appearance, but we hardly build probability density functions. In a structural approach it is not needed to represent more probable objects more frequently in the training set, but it is important to have the examples well distributed over the domain of the class. They should represent not the probabilities, but the possibilities of the objects in the class as well as possible jumps in the structural appearance [32]. The proposal made by Goldfarb and his colleagues as discussed here [19], [20] fits in this category.

During the past 20 years Goldfarb's group has developed the Evolving Transformation System (ETS) that represents a class of objects not just as a set of examples and a distribution of some features or attributes, but by their joint formative history. This is the way the 'shape', or structure (in the richest possible sense) of the observed objects developed out of the same root or primitive. A series of structural transformation steps describes such a development. In fact the set of transformations constitutes a class. Note that this is essentially different from some algebra or language of observable shapes. They try to generalize from what can be observed. The ETS is an attempt to describe the observations by an evolutionary history, which makes it entirely different from all currently available approaches. The latter try to answer to epistemological question, i.e. *how* we can build models that fit our class description. Goldfarb's group poses the ontological question, i.e. *what* a class of objects is on a deep level, concerning its creation.

In the next sections we will comment on some very specific aspects of ETS or on the discussions in papers that present it [19], [20]. These are:

- The special, entirely different definition of the concept of a class.
- Some remarks on the use of the formative history for class generalization.
- The discussion on the use of 'structs' (structural transformation primitives) instead of numbers as a basic mathematical concept.
- The possibilities to learn (the concepts of) classes and to build classifiers based on ETS.

The intention of this paper is to be a commentary on the ETS proposal. It will not explain ETS itself. It is thereby best to read it after studying the proposal itself. Readers who would like to get an impression of ETS by reading this commentary before they undertake this study are warned that they will thereby spoil the opportunity to build an independent view. This holds even stronger for readers who will just read this paper and possibly similar comments. For those who have not yet read the ETS papers, the following, personal opinion might be helpful.

The development of the ETS is a major effort. It can be judged as one of the most extensive enterprises ever undertaken in pattern recognition. It has been mainly done in isolation and it has not obtained much attention so far. This may have contributed to its very special characteristics. From the style in which the papers presenting the ETS are written it is clear that its primary author is strongly aware of the fact that he is undertaking something entirely new, perhaps revolutionary. Some readers might be shocked by some aspects of this, e.g. the heavy criticism of the areas of artificial intelligence and machine learning and by the way the novelty of the ETS project is emphasized. It would be a pity if this harmed the possibilities to understand, appreciate and criticize the proposals objectively. All this is clearly outside the mainstream paradigms of traditional pattern recognition. Still it may be very worthwhile to dive into it, just for the sake of seeing in which directions future pattern recognition projects may develop.

2. Object and class definition

An essential point in which the ETS approach to pattern recognition differs from almost all other approaches is in the definition of a class. It is defined in ETS according to its formative history. So objects that have been formed following a similar history belong to the same class and objects that have different histories belong to different classes. The consequences of this are large. As a result it positions ETS almost outside the current research as presented in the literature and on conferences.

Strictly speaking, the definition of classes according to their formative history implies that two almost identical characters, one printed by a laser printer on a sheet of paper, and one drawn by a piece of chalk on the blackboard belong to different classes. Or in another example, some coffee cups may be constructed by a machine from plastic, others may be shaped by hand from a piece of clay and then baked. A robot operating by ETS and instructed to fill the coffee cups, may fail, because its class of “coffee cups” is not existing or is just restricted to a particular subset. For the ETS robot, designed by the formative history, cups do not belong to the same class if their utility is similar, but only if the ways match in which they have been created.

The traditional class definition in pattern recognition is based on conceptual classes and not on natural classes. In our man-made world we often do not care how things are created as long as they share some utility. The classes live in the mind of man and our language has evolved to support that. Objects that belong to the same class have the same name (e.g. cup) as they share a concept (e.g. being a container for drinks) and not because they share a formative history. This is how in our cultural world language is constructed and how we communicate. Pattern recognition tries to imitate this human ability to deal with concepts. Thereby, in the design of many pattern recognition systems a supervised approach is taken: an expert names (labels, classifies) the objects and the pattern recognition system tries to find the pattern in the sensor observations of objects of the same class (i.e. having the same name). For instance, one needs to discover the pattern that all objects are used as containers in spite of their differences in building material.

The above problems may be solved in the following way. The formative history in the ETS system is defined by primitive transformations supplied by the user. He may avoid that insignificant physical differences play a role and will disturb the class definitions by not taking them into account in his definitions of the primitives. For the above example of character recognition, he has to supply primitives for the way they are written, e.g. how the hand moves, and has to neglect the physical properties of the material they are written on or are written with. As the temporal process of writing characters is very familiar, this is relatively easy. We all know how to write characters. In the example of the coffee cups this is more difficult. How can we describe how these cups have been shaped (truly or virtually, avoiding the differences between machine made and hand shaped cups). Here the danger arises that the shape will be described *as it is* and not the formative history.

A more complicated example than writing characters has been presented in [21] for describing body movements. Many detailed primitives are supplied for movements of the hips, the knees, the feet, etcetera. We wonder whether this was the original idea behind ETS. The temporal structure of the behavioral pattern may be carefully described, but this is not the evolution of this structure. Bio-physically, it may naturally have been evolved from crawling. On the contrary, one may also try to define it conceptually from just moving straightforwardly and then giving it a rhythm and adding more and more details for arms, legs and feet.

We like to stress the difference between the natural formative history as a physical ground truth and what we called here the conceptual formative history, which is a virtual reality as seen by some user. In the ETS papers these two views are called the formative history according to the *global concept* or according to an *agent's concept*. The first one may be useful for studying the natural sciences as it aims to build a representation the way objects evolved. This is not, however, what is traditionally studied in pattern recognition. There it is of interest how a user (an 'agent') judges the objects and he thereby should define the primitives accordingly.

From the biological point of view a whale belongs to the class of mammals and not to the class of fish, in spite of its fishy shape and in spite of the fact that in some languages the word for whale even contains ‘fish’. A whale is a mammal due to its natural formative history. Using a conceptual formative history, however, and ETS based pattern recognition system may be constructed that classifies a whale as a fish, e.g. focussing on a possible but not realistic evolution of the shape. So, the ETS system may be either used as a research tool in natural sciences or as an aid in society to construct systems that imitate a way the human recognition functions.

Like elsewhere in pattern recognition, classes may found in an unsupervised way from a given representation, or defined by the user supplied labels. The representation should allow to group objects, so a distance measure between objects mutually or between objects and classes should be defined. The ETS representation based on the formative history should therefor support the numeric comparison of objects by retrieving and comparing their individual formative histories, as well as the grouping of a set of formative histories (of objects belonging to the same class) such that formative history of an individual object can be compared with that of the class. The next sections will discuss the representation and the possibility to learn from it further.

3. Formative history

The idea to use the formative history of objects for their representation is original. This history, however, cannot directly be observed. It has to be derived from the object as it has grown into the presence using the set of primitive transformations supplied by a knowledgeable user. How to transform arbitrary sensors like camera’s or microphones for deriving the formative history has still to be developed. In fact they do point measurements by sampling objects in space or time. Structural sensors hardly exist.

Some applications in which ETS has been used illustrate this. It has been applied to analyze genome rearrangements as described in [22] and it has been used by Gutkin [23], [24], [25] to study phoneme recognition. The striking point of this last application is that it did not start from microphones (because oscillations in the air may have different formative histories as loudspeakers and human vocal cords), but instead used articulatory measurements, based on a sensor in the mouth, directly measuring its structural shape! The ETS study on human behavior (walking) assumes a direct measurement of angles. In many other approaches such angles are used as well, e.g. in studies on an automatic interpretation of the sign language [28]. Measuring them properly by just a set of camera’s, however, is an advanced computer vision problem.

For the time being it has been assumed that structural sensors exist. They will observe the object it its present, full grown state. Primitive transformations have to be found that explain them as evolved from a first primitive. The user has to define them on the basis of his knowledge of the problem. This may be compared with the definition of features in a feature based approach, or the definition of dissimilarities in a dissimilarity based approach [29]. Still there is a significant difference. Features and dissimilarities may directly be used to constitute a representation, as their definitions include the way they are measured. To derive, however, from an observed object and a set of transformations the formative history is not straightforward. It demands a minimization procedure to find to shortest formative history. As the mathematics around the structs is not yet fully grown, general procedures are not yet available. In the examples this is still done by hand [21]. Thereby, ETS, as it comes to us in its present state, is mainly a kit for building a simulator of the formative history. Automatic procedures for finding a representation of an observed object have to be studied further.

One of the aspects that make the formative history as an intriguing, and at the same time a difficult to obtain representation, is that it does not describe an object as a stand alone phenomenon (as done by features), nor by a pairwise comparison (as in the dissimilarity approach), but in its context of the entire set of other objects. Formative histories of objects can be shared, thereby reducing the complexity of the representation. Objects of the same class are expected to have a long shared formative history. Objects of different classes may deviate early from each other.

Due to the emphasis on a shared formative history, a class is in fact defined by a set of similar structural processes. So, an object is thereby almost a 'living thing', a structural process incorporating its own formation history. The concept of a class has to be learned or induced from a set of examples *in the presence* of other examples (possibly of other classes). Thereby it is possible to study the similarity of an object (i.e. a structural process) to a class (i.e. a class of structural processes). The similarity measure is thereby structural and not probabilistic, as it is related to the generation path (e.g. its length) of a process. An object may be classified as belonging to class A or B if the costs of generating it using the structural processes induced from the formative histories of class A are less than those of class B.

Consequently, ETS has the interesting ability to construct multi-level hierarchical processes: once a process is induced from a set of examples it may be used as a building block for more complex objects or classes. Here is a link to Occam's razor and MDL (Minimum Description Length) approaches [14]: there is no need to discover or describe the same path twice. If it is used many times in the same class, it thereby simplifies the class description [26].

One may wonder whether ETS really constitutes a pattern recognition system, or merely a system for pattern generation. It is emphasized on several places by the authors that it is important that the system is able to generate objects. Without doubt, this is certainly a very nice property as it will prove that the essentials of a pattern class are captured, once its members may be generated. But is this not far more than we want for recognition? We can recognize an oak, without being able to reconstruct one. Of course, we can take a seed and grow a new one, but we are in no way able to do this without a seed. We are even further away from growing it in a particular way, e.g. with branches that enable children to build a tree-houses in them. But this complete understanding is not needed for recognition and it would already be very useful to have a sensing device that automatically recognizes all tree types in a forest.

Like for the class definition, the use of formative history for object characterization objects deviates from what is needed to imitate the human ability to recognize patterns. Determining the formative history is a very ambitious aim that, once succeeded, will certainly be useful for a further development of the natural sciences. But it seems also to be much more than what is needed now to make an essential, progressive step in pattern recognition.

4. Shape, structure, numbers and structs

The analysis of what is needed for an appropriate representation of the shape and structure of objects seems to be by far the most valuable contribution of Goldfarb's research line. At an early stage he recognized both, the weakness of the traditional feature representation in vector spaces, as well as the need to derive more general and flexible tools than string languages and graph modelling [15], [16], [17]. The feature vector representation essentially reduces the object description. As a result entirely different objects can have the same representation, which can only be solved by statistical means [31]. Moreover, vector spaces isolate features from each other and from the object, neglecting its coherence and the object structure.

It is clear for Goldfarb, but not heavily emphasized in the present papers [19], [20], that a structural description is needed that is general, and generative in particular. On the latter aspect we commented above. A general structural description for coherent objects would make it possible to develop general flexible procedures for representation, generalization and recognition. It is argued that numbers are not sufficiently rich in order to fulfill this task. Instead an attempt is made to define *structs* in a similar way as numbers are defined by Peano. It is thereby a pity that it has not been recognized that the abstraction made by Peano deleted the structural concepts originally assigned to numbers in the human history. Like the 31 functions found in Russian fairy tales and analyzed by ETS [18], many more numbers return in myths and legends. Examples are 3 for life, 7 for time, 12 for space and 19 for awaking consciousness. This can be related in several ways to geometrical structures like triangles, cubes and pyramids. We admit that this does not solve in a straightforward way the need for transformative structural units as used in ETS, but we hold it for possible that numbers might be given again a richer interpretation useful for describing structures.

The proper definition of structs as a generalization of numbers such that interactions and transformations are included, is an important and responsible enterprise. Any proposal should be thought over and exercised in small examples. One should not be impatient. What we still do not understand from the present definition of the structs is that they have a set of discrete interconnection points. Moreover, evolution in ETS is assumed to proceed by discrete time steps by which we have a discrete set of structs. Is this an approximation? It seems to be based on the assumption that the world is really like that. Still, on the macroscopic level, what we experience and also scientifically try to describe is a continuous world. The structure we experience in objects is often global and continuous: it does not stop on a particular place, but integrates the entire object. If we start on the microscopic level with an assumed discrete nature, how is the transformation to a continuum made? Do we have to assume an infinite number of structs and interconnections points? It is admitted that there is no obvious better proposal, but there is a danger that the discrete definition of structs (in space and time) is still insufficient. Nevertheless, it should be judged as a possible major step forward.

5. Learning from examples

It has already been indicated above that ETS bears presently the characteristics of a simulator. It can be used by an expert to express his knowledge or assumptions, being tested and updated where it fails. In order to make it suitable as a pattern recognition system an automatic way to learn from examples is needed. So for a given set of primitives or structs defined by an expert, and an externally given set of examples, there should be an automatic way to learn the formative history of the objects, as expressed in the structs. This involves two problems to be solved:

- automatic object representation: determining the representation of individual objects
- training a classifier: determining the representation of an already labeled class of objects, such that new objects can be classified as good as possible.

The development of a strategy for learning still seems to be a very challenging task. In statistical pattern recognition based on feature representations this is done by the use of probabilities and distances. If we want to learn from structure the use of probabilities may be avoided: there is no additional information about structure if an (almost identical) copy of a particular object in the training set is found. If the concept of distances or dissimilarities is adopted as a criterion, learning may be defined in terms of optimizing the formative history such that the total path length of the generation process is minimized. This also minimizes the distance (path length) between an arbitrary object and the formative history description of all other objects. This MDL approach seems to be well suited for structural descriptions and transformations, but seems difficult to be optimized for an arbitrary set of structs.

In the unsupervised approach, classes may be defined as sets of objects (i.e. structural processes) with a similar representation. This implies that the total length of their formative histories is small. This may change, however, with the introduction of a new struct type. This problem is thereby as ill-defined as cluster analysis is: the result depends on the ‘metric’: new features or structs, or a small change of the operation of the ‘structs’ may change the results.

The supervised problem is somewhat better defined. If classes and structs are already known the formative histories of the classes may be defined such that the total formation path length within a class (total formative history) is small in comparison to the distances between class formative histories (may still be defined in several ways). This will result in a recognition system that can be applied to new objects. The weak point, however, is that in this supervised approach the classes are pre-set on the basis of expert knowledge and do not necessarily a priori coincide with similar formative histories, which was a basic assumption in the design of ETS. If this happens there is a mismatch between the labels supplied by the supervisor and the way he defined the structs. It should not happen, but it may happen, as the first are based on his conceptual knowledge of the classes and the second on his insight into the way an object may have been shaped. This problem seems to be more severe for ETS than for traditional feature based systems. It is more difficult for an expert to phrase how objects may have grown into existence than to make explicit on what features they may have defined their labeling.

On the whole, the characteristic of ETS learning will be non-probabilistic, based on distances. It thereby bears a resemblance with what has been called elsewhere ‘domain based classifiers’ [31], [32].

6. Discussion

The main characteristic of the ETS proposal is the special, novel definition of a class, based on a natural formative history instead of a concept adopted by an expert. This has two consequences. First, its application emphasis will be different from the traditional pattern recognition research. It should focus on applications in which knowledge is available on the way objects found their structure. This knowledge may be real, e.g. physically, or more virtual. In the latter case it is based on an imagination how the structure may have grown, treating particular physical differences as insignificant invariants. Second, as the natural classes are not known, but have to be defined by the natural formative history, it puts ETS in the ill-defined corner of cluster analysis: goals (classes) and means (the representation) are mixed and have to be optimized simultaneously.

Our second concern is about the input data. There are no real structural sensors yet. There is always a local point measurement of intensity, pressure, position, etcetera. Sensors output primarily numbers. We can wait for structural sensors to arrive, but it has to be doubted whether they will be developed soon. Hence it might be worthwhile to consider to develop ‘virtual’ structural sensors, e.g. the outcome of an image sensor converted from pixel intensities to primitive structs: the first level of a structural representation, e.g. a multi-scale representation that connects every point in the image with every other point. This is, however, not scientifically different from the use of (a set of) filtered images, e.g. a multi-wavelet representation, and raises a third concern.

ETS is initially phrased as a structural representation. We already wondered whether structural processes can be modelled by a set of discrete interactions, sampled by discrete time steps. For computer implementations such a discretization is, of course, necessary, as we do not have continuous computers, neither in space (memory) nor in time (CPU). Data storage and programming are essentially discrete. How to deal with a continuous concept like structure? At the end we have, of course, to deal with discrete numbers, having a finite, discrete accuracy and isolated from all others. So everything we do will just be an approximation of the structure. How different is this from the present approaches that are based on local neighborhood features and already take into account the relation of object points with their neighboring points (in space or time or frequency). Maybe we will find out that it is not very different when ETS is fully worked out, but maybe it is a starting point towards a very different theory.

As a conclusion we state that the ETS approach is intriguing and very ambitious. It has set some goals and assumptions that may not be very realistic, however. If we push it too hard, we may end up with an approach that is very close to what we already do, but formulated in an entirely different way. The main fruit of this research line might be the renewal of the description of problems and their solutions is renewed. There is, however, also still the perspective of something that is really novel and will open entirely new challenges and approaches: learning what structure is, learning the structure itself and learning from the structure.

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