Computational Intelligence for Geo-science

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SUMMARY

We introduce computational intelligence technologies, especially, neural networks, fuzzy systems, and evolutionary computation, for researchers in geo-science to help them to apply these technologies to their fields. Following the general introduction of each technology, we explain how these technologies handle nonlinearity, how to deign these nonlinear systems, how to acquire knowledge from observed data, what kind of feature they have, and how to embed expert's knowledge in the systems. We demonstrate three examples of computational intelligence techniques applied to geological inversion, estimation of rock location and density from their gravity responses, and designing image enhancement filters.

Keywords: computational intelligence, neural networks, fuzzy systems, evolutionary computation, nonlinear systems

INTRODUCTION

Artificial neural network (NN), fuzzy system (FS), and evolutionary computation (EC) are typical technologies in computational intelligence and are applied to nonlinear tasks and optimization tasks.

NNs are network model of biological neural networks consisting neurons. Artificial neuron models multiple inputs and one output, the switching function of neurons, and the adaptive synaptic weights of a biological neuron. The biggest feature of the NNs is to have nonlinearity created by the nonlinear basis function of a switching function of each neuron and learning capability created by adaptive synaptic weights and learning algorithms. Due to the learning capability, the NNs easily obtain the nonlinear relationship between input and output data.

FSs consist a fuzzy rule base and a reasoning engine. The fuzzy rule base consists fuzzy rules that describe qualitative logic and membership functions that define fuzziness in the fuzzy rules. The boundary of the rule areas is not sharp but *fuzzy*, so that multiple fuzzy rules are activated by one input value set. The rule strength, the activation level, is determined by membership values and fuzzy logic operators, and the final output value is determined by all activated rule outputs by weighting with the rule strengths. These features realize nonlinearity and smooth change of system outputs. Other important feature is that we can easily handle explicit qualitative logic, which allows us to embed human knowledge or acquire knowledge.

EC is searching or optimization algorithm inspired by biological evolution. Typical paradigms consisting of the EC include GA (genetic algorithm), ES (evolution strategies), EP (evolutionary programming), and GP (genetic programming). The features of the EC are that its search or optimization is conducted:

(1) based on multiple searching points or solution candidates (population-based search),
(2) using operations inspired by biological evolution, such as crossover and mutation,
(3) based on probabilistic search and probabilistic operations, and
(4) using little information of searching space, such as differential information.

Good news of the EC is that it quickly converges to near global optimum, but bad news is that it takes long time to reach to the exact global optimum, in general.

After understanding the above general features of the three techniques, we describe their several aspects that are useful for geo-science in the following sections.

HOW NN AND FS REALIZE NONLINEARLITY?

Suppose to train an NN consisting four hidden neuron nodes using five training data specified as circles in Figure 1. Each neuron has a sigmoidal function characteristic, and the sigmoid functions are amplified and shifted by synaptic weights and combined to form the final NN output. Compare four outputs of hidden neuron nodes in the right lower and total NN's output in the right upper in Figure 1 to understand that total nonlinear function is formed by combining the four modified sigmoid function.

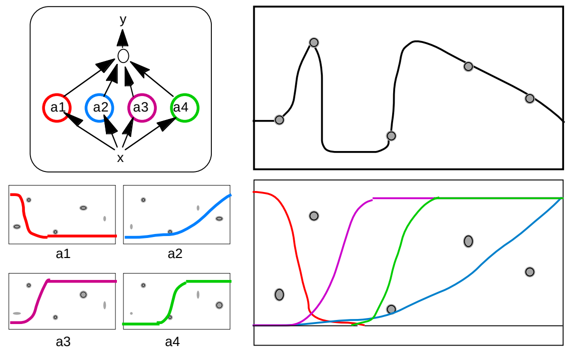

Figure 1. Combining four sigmoid functions that are amplified and shifted by synaptic weights approximates a nonlinear function.

Let's approximate the same nonlinear function using an FS. The essential point of rule-based systems is to partition an input space. The FS fuzzily partitions an input space with membership functions that determine the degree how input values belong to each rule. Figure 2 shows the example of fuzzy partitioning of an input space. As each rule outputs are weighted by rule strengths, and the final FS's output is calculated as the weighted average of each rule outputs.

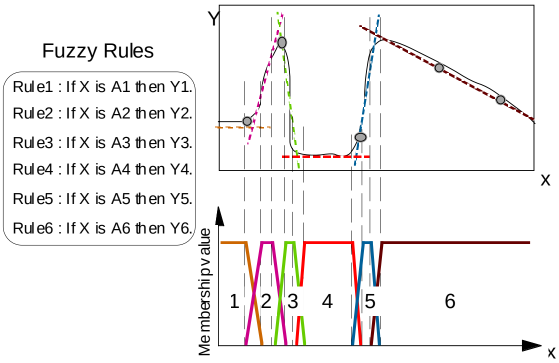

Figure 2. Combining six rule outputs approximates a nonlinear function. The output of the boundary of rules is calculated by weighting each rule output with rule strength obtained by membership values

AUTO-DESIGNING NONLINEAR SYSTEMS

Suppose three cases when we design nonlinear systems: (case 1) we know input—output data and want to design a system that generates the output data from the input data; (case 2) we do not know input data but a system and its system output, which is the case of inversion problems; (case3) we do not know either input data or a system, and the system output is hard to evaluate automatically while human experts can.

In (case 1), there are three approaches: mathematical approach, neural approach, and rule-based approach (see Figure 3). Auto-designing all these approaches is supported by the EC techniques, such as GA and GP, and NNs.

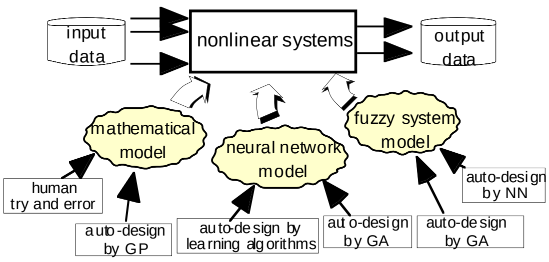

Figure 3. Three modeling methods to auto-design nonlinear systems based on computational intelligence approach.

In (case 2), EC searches the best input data that create the observed or given output data. Geological inversion problems that geologists sometimes have tried to find the best input data with try-and-error method is in this case.

The (case 3) is the best case to use Interactive EC (IEC) where human evaluates the system output and the EC optimizes the target system according to the human subjective evaluation. When system outputs are image, animation, or sound, sometimes we need the help of expert's knowledge and experience. The IEC is the way to embed them into the system optimization. We show this example in geological inversion in the application section later.

There are two auto-designing methods for nonlinear systems: parametric optimization of the system and evolving the system. The parametric optimization is the method to tune the parameters of the nonlinear systems. If the system is modeled by mathematical equations, it is easy to imagine tuning the parameters in the question using the EC or gradient methods. NNs and FSs are parameterized and optimized using the EC and gradient methods, too. Synaptic weights of the NNs are the system parameters to be optimized, and shape parameters of membership functions and rule outputs of the FSs are those to be optimized, too.

On the other hand, the evolving-systems generates mathematical equations, NNs, or FSs according to the performance of the previously evolved systems in previous generations. The GP is a method generates equations, the GA is used to configure the size of NNs, and fuzzy classifier that is a GA-based rule generation methods generates FSs.

DATA MINING, KNOWLEDGE EMBEDDING, AND NEURO-FUZZY SYSTEMS

Data Mining or Knowledge Acquisition

Data mining or knowledge acquisition is to acquire knowledge from numerical data. Although statistics provides us the tendency or characters of the data, it does not explain the meaning of the data or does not predict what happens next from the past data.

The FSs trained by EC or gradient methods using data can explicitly explain the data. In the case of the (case 1) in the previous section, the trained FSs explain the mapping relationship from input space to output space.

If explicit knowledge acquisition is not, the NNs learn the relationship between input and output data, and we can use the trained NN as an implicit knowledge system. This approach is used for pattern recognition, prediction and others.

The midterm method of the above explicit and implicit knowledge acquisition is to obtain mathematical equations that explain the relationship using the GP. As these data mining approaches are based on approximation, $f = ma+0.001sin(m)/\{cos\ (a)-0.3\}$ might be obtained as Newton's law instead of $f = ma$.

Knowledge Embedding

As FSs handle qualitative rules in IF-THEN form, it is easy for us to directly describe our knowledge on the given tasks. Suppose to control a pole-pendulum, for example. Even if we are not control engineers, we know: *IF pole angle is small, THEN force is a few*, *IF pole angle is big, THEN force is big*, and so on. This rough explicit knowledge on the given task becomes good initial situation of system optimization and accelerates the optimization comparatively random initialization. The qualitative knowledge that are normal case of our knowledge is described in fuzzy logic rules, and the description of fuzziness, such as *a little* or *big*, is determined by learning using EC or gradient methods.

Neuro-Fuzzy Systems

When we have perfect knowledge on the given tasks, rule-based systems are the best to solve the tasks. If we do not have such knowledge but many data, learning systems such as NNs are the best. When we have partial knowledge on the given tasks and numerical data, how to handle them? Even if the knowledge is imperfect, it is much better than nothing.

Neuro-fuzzy systems that are the combination of NN and FS is one of your choices. First target systems is described using FS based on your imperfect knowledge, then the imperfect parts are fine-tuned using learning capability of the NN and obtained training data.

So many consumer products and industry systems based on the neuro-fuzzy systems have been put on the market since early 1990s (Takagi, 2000b).

INTERACTIVE EC

When the system output is not numeric data but image, movie, sound, or stimuli to human five senses, it is hard for computers to evaluate how the system output is good. As numerical evaluation is required to be fed back to optimize the target system in system optimization mentioned in this paper, human cooperation is requested for such systems.

The IEC is an EC that optimizes systems based on human subjective evaluation. The "based on subjective human evaluation" does not mean unreliable but rather positive. Human expert's judgment or evaluation based on his or her knowledge and experience can be directly reflected to the system optimization. The geo-scientific applications in the following section are such case.

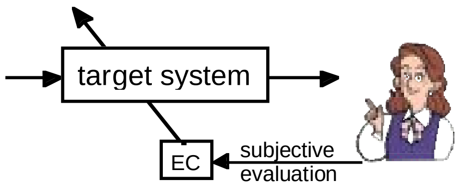

Figure 4. Interactive EC that is a system optimization by EC based on human subjective evaluation.

The IEC application fields include graphic arts and animation, 3-D CG lighting, music, editorial design, industrial design, facial image generation, speech processing and synthesis, hearing aid fitting, virtual reality, media database retrieval, data mining, image processing, control and robotics, food industry, geo-science, education, entertainment, social system, and so on (Takagi, 2001).

APPLICATIONS OF COMPUTATIONAL INTELLIGENCE

So many applications of NN, FS, EC, and their combinations have been presented and used in our real world. In this paper, we introduce some geo-scientific applications among them.

The geological inversion problem is the task to estimate the best matched and reasonable geological scene. What we know is a mathematical forward code and we need to give initial condition that results the best simulation outputs. As we monitor the system outputs and decide the initial conditions, this task is called inversion problem. This task was time-consuming due to the try-and-error approach.

The IEC was applied to this task (see Figure 5) (Boschetti et al., 1999; Boschetti and Moresi, 2000; Wijns et al., 2001). As this task is an optimization task, human random search of initial conditions should be replaced with optimization methods. Problem is that the only human experts can evaluate and it seems hard for conventional optimization techniques to automate the optimization. The IEC solves this problem.

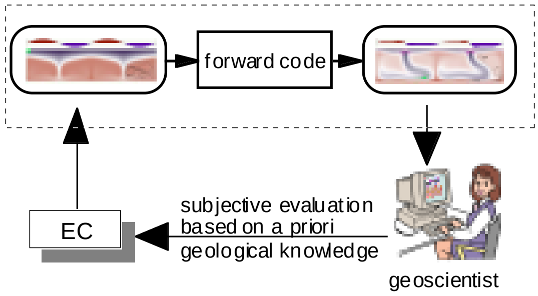

Figure 5. IEC-based geological inversion. The expert evaluates the forward code outputs, and the EC finds the best matched input data based on the expert's evaluation.

The second application is an exploration geophysics task; it is to reconstruct the distribution of rocks underground from the gravity measurement of the rock on grand surface (Boschetti and Takagi, 2001). Figure 6 shows the example of this task. In practical task, other physical properties such as seismic data, gravity, electric, and magnetic measurements besides the gravity will be used.

Difficulty of this task is to estimate multiple parameters of density, depth, and size of the rock from one-dimensional data. , Mathematically, this task has non-unique solutions. To reduce the possible solutions, we need geologist's knowledge.

We applied the GA and Visualized GA (Takagi, 2000a; Hayashida and Takagi, 2000) to this task (Boschetti and Takagi, 2001) and compared their performance. The Visualized GA is a combination of GA search and visualization of the landscape of GA space. Human visually cooperates with GA search to accelerate the optimization.

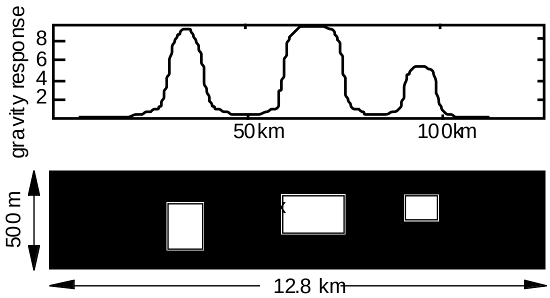

Figure 6. Simulation task to reconstruct the distribution of rocks underground from the gravity measurement of the rock on grand surface.

The third application is image processing or enhancement. We want to deign an image enhancement filter that enhances image to visually help human to detect certain features. The difficulty of this task is that only human evaluates how the enhanced images are visually easy to detect the features.

The IEC-based filter design solves this task by combining the subjective evaluation of human visual inspection and automatic optimization of the filter design.

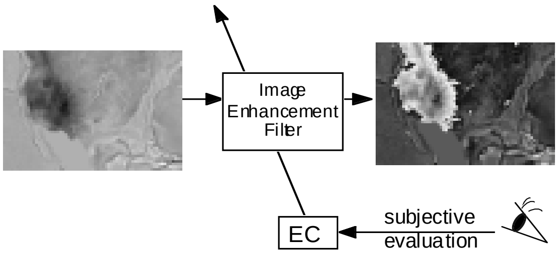

Figure 7. Example of IEC-based filter design.

CONCLUTION

In this paper, we introduced NNs, FS, and EC as representative computational intelligence techniques and how to use them for geo-scientific tasks with three examples. Introducing techniques in other field sometimes leads dramatic progress in the field. We hope that this paper becomes such a trigger to geology and geophysics.

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