

Rule Extraction from Active Contour Classifiers

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Abstract. *In this paper, the idea of rule extraction from active contour classifiers is presented. The concepts are new in relation to active contour approach. The problem is illustrated by examples having roots in technical diagnosis and in analysis of content of images.*

Keywords: *active contour approach, rule extraction, classification, decomposition rule extraction.*

1. Introduction

It is well-known that humans are comfortable considering and dealing with rules that are represented as a hypercube with axis-parallel planes in the variable space. It allows human to explain the phenomenon under consideration and to learn about relation cause-outcome. One meets such reasoning approach daily, and a good example of practical importance are medical and technical diagnoses. In Section 2 a brief look into a case illustrating the latter one is given.

The paper is organized as follows. As mentioned, first the practical example of rule-based system is presented. Next, the mutual relation between classification and active contour approach is described. Finally, concepts of rule extraction from results obtained by application of active contour approach are presented and discussed.

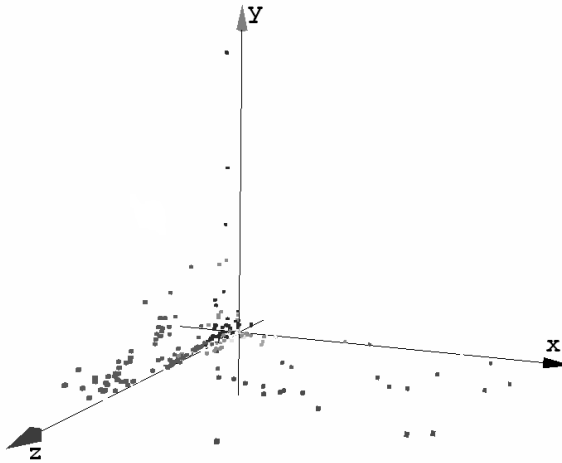


Figure 1: Exemplary DGA measurement results (x, y, z)

2. Practical Importance of Rule Representation of Knowledge-Example

According to the internationally acknowledged standard IEC [1], three variables (x, y, z) are used to reason about possible state of the power transformer of certain type. They are defined as the following ratios

$$x = \frac{C_2H_2}{C_2H_4}, \quad y = \frac{CH_4}{H_2}, \quad z = \frac{C_2H_4}{C_2H_6} \quad (1)$$

where H_2 , CH_4 , C_2H_2 , C_2H_4 , C_2H_6 denote the amount of hydrogen, methane, acetylene, ethylene and ethane in a gas under examination (in ppm units - parts per one million), respectively, all of them are measured on the examined object (power transformer).

Within the IEC-procedure, the values of (x, y, z) are coded with the use of three integers $\{0, 1, 2\}$ as shown in Table 1.

Consequently, each triple (x, y, z) of real values can be transformed into related coded triple (c_x, c_y, c_z) of three integers $\{0, 1, 2\}$. In terms of diagnosis, there are nine classes d_k of the state of power transformer that are well-defined from the

Table 1: IEC coding

value/quotient	$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_4}$	$\frac{C_2H_4}{C_2H_6}$
[0, 0.1)	0	1	0
[0.1, 1)	1	0	0
[1, 3)	1	2	1
value ≥ 3	2	2	2

engineering point of view and additionally one has one class that contains ambiguous cases. Linguistically, $d_k (k = 1, 2, \dots, 10)$ are called as follows:

1. No fault,
2. Partial discharge of low energy,
3. Partial discharge of high energy,
4. Disruptive discharge of low energy,
5. Disruptive discharge of high energy,
6. Overheating below 150°C,
7. Overheating between 150°C and 300°C,
8. Overheating between 300°C and 700°C,
9. Overheating over 700°C,
10. Unidentified.

Every triple (x, y, z) and consequently (c_x, c_y, c_z) enables reasoning about the technical condition of the examined transformer, i.e. giving the diagnostic statement d_k . For visualization, a different colour of a grey level may be assigned to each cuboid C^k related to class d_k (Fig. 2).

One can observe that IEC system divides the three-dimensional decision space into a number of disjoint areas in the form of cuboids C^k , with the largest volume being occupied by the space of unidentified transformer's conditions.

The expert knowledge encapsulated in the IEC standard can be also represented by the form of logic rules:

$$\text{IF code } (c_x, c_y, c_z) \text{ THEN the transformer's condition is } d_k. \quad (2)$$

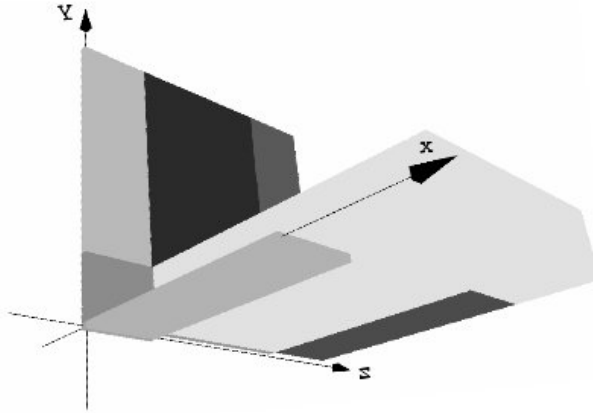


Figure 2: Visualisation of the IEC classification

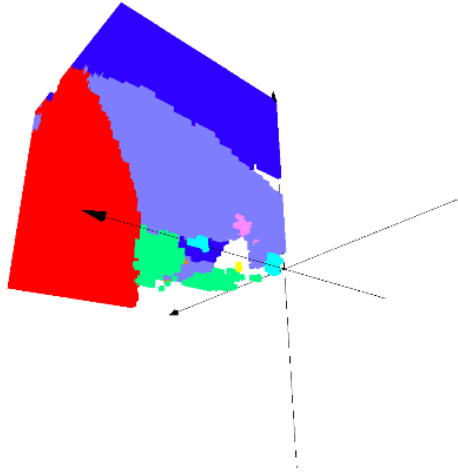
These are the rules of crisp logic, which are unambiguous and mutually exclusive. Note that the form and number of rules is comfortable for humans.

In terms of (x, y, z) , the rules (2) - not applied in the IEC standard - can formally use cubes with axis-parallel faces in the variable space, i.e.:

$$\text{IF } (x, y, z) \in \text{cuboid } C^k \text{ THEN the transformer's condition is } d_k. \quad (3)$$

However in the reality, regions dedicated to classes d_k are of irregular shapes and they are not precisely common for every power transformer. To deal effectively with this problem, since the implementation of IEC and other national standards, novel methods have been proposed [2, 3, 4, 5, 6, 7, 8], like the use of soft computing technology or even k -NN. In these methods, the partition of the decision 3D-space spanned by axis x, y, z into the ten decision regions is performed on the basis of real measurements and of verified diagnostic statements d_k^{verified} obtained by inspection of a switched off transformer - for exemplary result see Fig. 3.

To the best knowledge of authors, so far no active contours methods have been applied to improve solution of this diagnostic problem.

Figure 3: Results of k -NN method

3. Classifier vs. Active Contour

Let us use the following notation:

- L - a finite set of labels, $L = \{1, \dots, N\}$;
 - N - a number of classes;
 - l - a label;
 - O - a given set of points.
- (4)

The classification problem can be formulated as the task of assigning a proper label l from the finite set of labels L to each object o from the given set O . Such an assignment can formally be described as a classification function (classifier) $k : O \rightarrow L$ (each object $o \in O$ receives a unique label $l \in L$).

In general, there are many functions $k \in K$ that map O into L , where K denotes a set of all possible classifiers in a given problem. Consequently, the need for choice or construction of an optimal classifier emerges.

Request for optimality is usually formulated in the form of performance index $Q : K \rightarrow R$. Thus, the construction of optimal classifier becomes the task of optimization of performance index Q [9, 10, 11, 12]. To find an optimal classifier, every method based on some a priori knowledge (e.g. on a training set of correctly labeled objects) may be applied. That knowledge can be expressed in the form of performance index $Q : K \rightarrow R$ capable of the evaluation of the usefulness of each

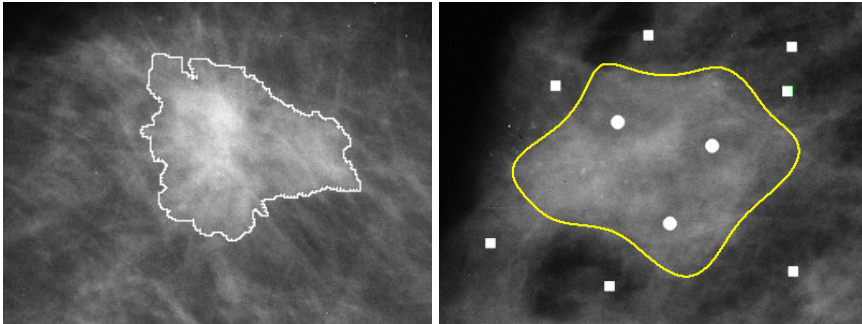


Figure 4: Localization of objects by active contour methods - examples

function $k \in K$. It is further assumed that $k : X \rightarrow L$ where $X \subset R^n$ denotes a feature space.

In the *active contour* approach, the contour of the object is sought in an optimization process of a performance index called energy function $E : C \rightarrow R$, where C is the space of acceptable contours. Originally, *active contour* methods [9, 10, 11, 12, 13] were developed as tools for the low-level image segmentation. The "*active contour*" term was first proposed in [9] and defined as a parametrized curve (called snake). The contour evolves in the examined image in the way that the energy function is optimized. The form of energy should enable localization of the visible object or detection of region of certain characteristics - Fig. 4.

Hypercontour h is understood as a generalization of contour, because contour is a special case of hypercontour for $N = 2$ (object and background) and $n = 2$, where n denotes dimension of the vector of analyzed data, and image is a case of $n = 2$. It is easy to generalize the active contour technique and speak about the active hypercontour technique [13, 14]. Here, the energy function $E : H \rightarrow R$ must be properly defined to evaluate the generated hypercontours $h \in H$ (where H is the space of all the available hypercontours) and the chosen optimization technique must be able to find the optimal classifier. The energy function plays here a similar role to performance index $Q : K \rightarrow R$ which evaluates classifiers. The hypercontour approach can be applied to multidimensional classification problems which are not the image segmentation tasks in the classic sense, see e.g [15].

In [14] it has been proven that hypercontours are equivalent to classifiers. Each classifier generates a hypercontour in every feature space which has a sufficient discriminative power to distinguish classified objects. Also each hypercontour unambiguously generates the corresponding classification function. The relationship

between those groups of methods was presented in [16] and the general formal definition of hypercontour is formulated in [16] and [14].

4. Concepts of Rule Extraction

Rule extraction from results of data analysis is a research field of data mining and knowledge discovery. Research is mostly divided into two categories: pedagogical or decompositional [17]. The first one is based only on data and feature space, without the need of any classifier. An example of a pedagogical method can be the TREPAN algorithm [18]. Decompositional methods are based on gaining knowledge about data from a given classifier. Extraction of rules from artificial neural networks [19, 20, 21, 22] or from support vector machines [17] are examples of the tasks of this kind. To the best knowledge of the authors, so far no decompositional techniques for rule extraction have been developed for active contour methods. Below some possible approaches are presented.

From Section 3 follow two remarks which are important in the context of the topic of this paper:

1. Each classifier generates a corresponding hypercontour in the proper feature space.
2. Each classifier assigns labels to vectors from the feature space and divides it into N regions of different topology. The boundaries of those regions are in fact a visual representation of a hypercontour.

It may be of interest to extract knowledge in the form of logical rules which are related to the labeled regions. However, the problem is that the regions are of shapes generated by hypercontours, and the shapes may be irregular, cf. medical images presented in Fig 4. If this is the case, the obtaining of a small number of simple, human-friendly rules in the form similar to (3) may be not possible when the precision in the knowledge representation is required.

Let us illustrate the problem on the two-dimensional problem where one region of irregular shape approximately determined by an active contour has been detected - Fig 5.

Proposition 1 *Minimum of the error of coverage of the region detected by active contour and simultaneously the minimal number of rules. The knowledge is extracted after the region has been found.*

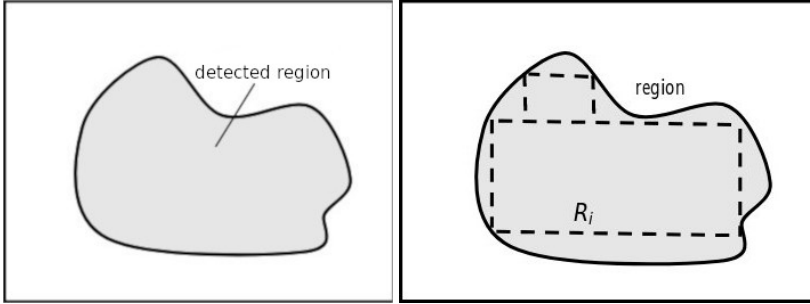


Figure 5: Example of contour

Let:

$$\begin{aligned}
 A_r & - \text{area of the region determined by active contour,} \\
 S_i & - \text{area of each } i\text{-th rule rectangle,} \\
 N & - \text{number of rectangles } R_i \text{ used for rules' description.}
 \end{aligned} \tag{5}$$

The system of rules is of the form:

$$\text{IF } (x, y) \in \bigcup_{\{i:L_i=l\}} R_i \text{ THEN the label is } l, \tag{6}$$

where R_i denotes i -th rectangle and L_i denotes label connected with that rectangle. Minimum of the value of $|A_r - \sum_{i=1}^N S_i|$ is expected for precision of the coverage. The absolute value $|\cdot|$ is used because the region can also lie insight of the set of rectangles, similarly to the concept of rough sets. However, to make the rule system (6) human-friendly and interpretable, generation of possible small (but no less than one) number N of rules is recommended. Consequently, the performance index is composed of two elements to be minimized, namely $|A_r - \sum_{i=1}^N S_i|$ and N .

Note, that in the Proposition 1, there is no direct relation to the type of active contour. The next method is dedicated to the *adaptive potential active hypercontours* [13, 14]. The definition of *adaptive potential contour* is as follows [15]:

Definition 1 Let feature space X be a metric space with a metric $\rho : X \times X \rightarrow R$. The potential hypercontour is defined by means of a set of labeled control points: $D^c = \{(x_1^c, l_1^c), \dots, (x_{N^c}^c, l_{N^c}^c)\}$ where $x_i^c \in X$ and $l_i^c \in L$ for $i = 1, \dots, N^c$. Each

point is a source of potential the value of which decreases with increase of distance from the source point. The classifier k (and consequently the corresponding hypercontour h which it generates) is defined in the following way:

$$\forall_{x \in X} k(x) = \operatorname{argmax}_{l \in L} \sum_{i=1}^{N^c} P_{\Psi_i, \mu_i}(X_i^c, x) \delta(l_i^c, l), \quad (7)$$

where $\delta : L \times L \rightarrow \{0, 1\}$, $l_1 \neq l_2 \Rightarrow \delta(l_1, l_2) = 0$, $l_1 = l_2 \Rightarrow \delta(l_1, l_2) = 1$ and $P : X \times X \rightarrow R$ is potential function e.g. exponential potential function:

$$P_{1 \Psi, \mu}(x_0, x) = \Psi e^{-\mu \rho^2(x_0, x)} \quad (8)$$

or inverse potential function:

$$P_{2 \Psi, \mu}(x_0, x) = \frac{\Psi}{1 + \mu \rho^2(x_0, x)} \quad (9)$$

In both cases $\Psi \in R$ and $\mu \in R$ are parameters characterizing the potential field. Those parameters and the distribution of control points fully describe the classifier.

For clarity of presentation the approach is illustrated on the two dimensional case.

Proposition 2 *There are two kinds of control points: the first ones lie in the interior of the region (circles) and the second one - in the background (squares), see. Fig. 6. It is possible to change their parameters, positions, as well as their number. The more complicated the shape of the object to be detected, the more control points are needed, and also the more rules must be generated for description of such object.*

For this reason, the number N of rules is assumed to be equal to the number of control points, though another proposition can be considered.

The proposition is: If the rules need to determine the label I_b of the background, then the number and position of outer control points (green) are considered, but if the rule systems is created for description of the region interior then the 'red' points are basis for rules' formulation.

Of course, there are many ways to relate (conceptually and computationally) the rectangles of rules with the current position of control points.

Two approach are possible:

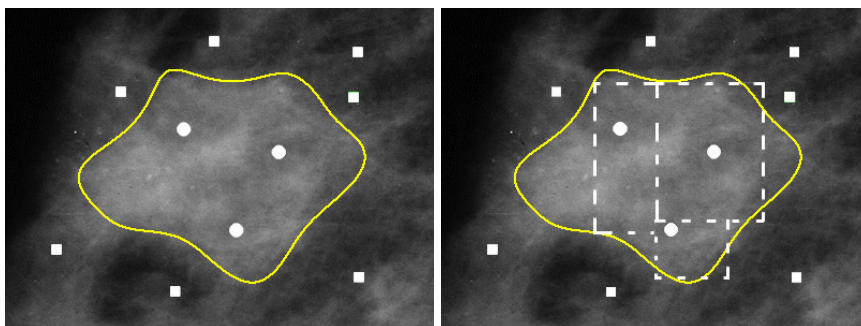


Figure 6: Example of potential active contour with control points highlighted (left) and three exemplary rules based on three interior control points (right).

1. *The rules' system is generated after the region has been found, i.e. the evolution of contour is finished - Fig. 6. This is an obvious method and it is recommended because the task of searching object and the knowledge extraction are separated procedures.*
2. *The quality of classification performed by the rules' system is evaluated during the evolution of the active contour and the knowledge extraction process affects the precision of the object detection. The latter observation induce to prefer the approach 1.*

5. Outlier Regions and Rules

Geodesic Active Contours [11] and potential active contours [13, 16, 14, 15] in a natural way may generate disjoint contours and subregions in the analyzed space. The advantage of these methods is the simultaneous detection of many objects is possible, like the two eyes in Fig. 7. It may occur that one sub-region dominates with the respect to its area or number of classified objects and the other one or ones are of less importance because of the "volume" of data or information involved - Fig. 8.

When rules are generated for the obtained sub-regions A and B then the rule or a number of rules assigned to the sub-region B can be interpreted as the dominating one, while the sub-region A - as the marginal or outlier one. The distance of the small sub-region from the dominating one is also of importance to justify the

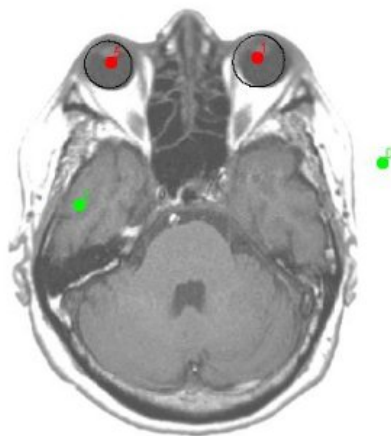


Figure 7: Result obtained by potential active contour.

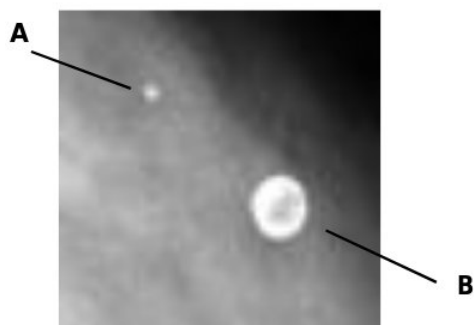


Figure 8: Two sub-region of different size

use of the notion 'outlier'. The same approach and motivation is valid in multidimensional space. However, the real importance of the knowledge extracted can be stated by the expert knowing the problem under examination.

6. Conclusions

In the paper, the problem of extraction of rules describing the regions being result of the data analysis performed by active contours is considered. Two basic

concepts for rule extraction are presented and their advantages or weaknesses are pointed out. Some illustrative examples in the three- and two-dimensional spaces are shown. It is evident that an optimization is necessary to find the balance between the precision in knowledge representation and the number of rules which is comfortable for humans.

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