Possibility of the Rough Set Approach in Phonetic Distinctions

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Abstract

The goal of automatic speech recognition is to study techniques and systems that enable agents such that computers and robots to accept speech input. However, this paper does not provide a concrete technology in speech recognition but propose a possible mathematical tools to be employed in that area. We introduce rough set theory and suggest the possibility of the rough set approach in phonetic distinctions.

I. Introduction and Preliminaries

This paper deals with the possibility of the rough set approach in speech recognition. Actually, the rough set approach is based on knowledge of an agent about some realty such as acoustic knowledge with phonemic knowledge, lexical knowledge, syntactic knowledge, semantic knowledge and even pragmatic knowledge and his ability to classify related data obtained from observation, measurements, etc.. This chapter is concerned with rough set theory used in our study. Let U be the universe set of objects we are interested in and A be the set of all attributes considered in speech recognition. An attribute $a \in A$ is a total function $a : U \rightarrow V_a$, where V_a is the set of values of a, called the domain of a. With each attribute $a \in A$, we can associate an equivalence relation $R(a)$, which is defined by $R(a) = \{(x, y) \in U^2 | \ a(x) = a(y)\}$. For every subset of attributes $B \subseteq A$, let IND(B) be the equivalence relation $\{(x, y) \in U^2 | \ a(x) = a(y), \ \forall a \in B\}$. That is, IND(B)= $\bigcap\{R(a) \mid a \in B\}$. By a knowledge base we can understand a system $K = (U, A)$. For any $a \in A$, by U/a we mean the partition of X, $U/R(a)$. If $B \subseteq B' \subseteq A$, $U/\mathrm{IND}(B')$ is a refinement of $U/\mathrm{IND}(B)$, That is, every element of $U/\mathrm{IND}(B)$ is expressed as a union of some elements of $U/\mathrm{IND}(B')$. For any $a \in A$ and $x \in X$, $[x]_a$ denotes the set of all elements of X whose values under a are equal to $a(x)$. In fact, $[x]_a$ is the equivalence class $[x]_{R(a)}$ of x under $R(a)$. A knowledge base $K=(U,A)$ is said to be complete if for any $x \in X$ $[x]_{R(A)}$ is a singleton, where $R(A)$ denotes IND(A). A set $X \subseteq U$ is a-definable ($a \in A$) if X is the union of some equivalence classes of X under $R(a)$. In complete knowledge base $K=(U,A)$, every singleton of X is A-definable. If a set $X \subseteq U$ is not a-definable, then we call X a-rough. For any $X \subseteq U$ and $B \subseteq A$ we define two interesting sets as follows:

$$B_*X = \bigcup \{ Y \in U/R(B) | Y \subseteq X \}$$

$$B^*X = \bigcup \{ Y \in U/R(B) | Y \cap X \neq \emptyset \}$$

called the B-lower and B-upper approximation of X, respectively.

We find that a set X is B-rough if and only if $B_*X = B^*X$ and that X is B-definable if and only if $B_*X = B^*X$. An attribute $a \in A$ is dispensible in the knowledge base K if IND(A) = IND(A-{a}). If each $a \in A$ is not dispensible, then we call the set A of attributes independent in K. If A is independent in K, then any subset of A is independent. A subset $B \subseteq A$ is call a reduct of A, denoted by $RED(A)$, if each $b \in B$ is not dispensible and IND(B) = IND(A). The set of all attributes which are not dispensible in K is call the core of A and denoted by $CORE(A)$. Then, we have the following important relationship between the core and reduct: $CORE(A) = \bigcap RED(A)$. If an attribute set B is said to be dependent on an attribute set C in a knowledge base K if IND(C) $\subseteq$ IND(B). It is easy to show that B is dependent on C if and only if IND($B \cup C$) = IND(C), equivalently $C_*X = X$ for all $X \in U$/IND(B). Now, we have the following proposition:

Proposition 1.1 Let B and C be attribute sets in a knowledge base $K=(U,A)$.

(1) If B is a reduct of C, then $C-B$ depends on B and IND(B) = IND(C).

(2) If B is dependent, then there exists a subset $C \subseteq B$ such that C is a reduct of B.

2. Significance of Attributes

The importance of attributes can be preassumed on the basis of auxiliary knowledge and described by generally accepted weights in the analysis of issues being considered. In rough set approach, we avoid any preassumed knowledge aside from a knowledge base $K=(U,A)$ and compute the classificatory power of some attributes. Let B and C be subsets of attribute set A in K. Then, the B-positive region of C, denoted $POS_B(C)$, is the set of all objects in U which can be properly classified to some classes of U/IND (C) employing knowledge expressed by the classification U/IND (B). That is, we have

$$POS_B(C) = \bigcup \{ B_* X \mid X \in U/C \}$$
$$= \bigcup \{ x \in U \mid [x]_B \subseteq X \text{ for } some\ X \in U/C \},$$

where for the sake of convenience we write U/C to mean U/IND (C). We say that $b \in B$ is C-dispensable in K if $POS_B(C) = POS_{B-b}(C)$. We

define the dependency degree of C on B, denoted by $\gamma_B(C)$, as follows:

$$\gamma_B(C) = card\ \ POS_B(C)/card\ \ U$$

If $\gamma_B(C) = 1$, we say C totally depends on B and we recognize all objects of U can be classified to classes of U/C in terms of knowledge B. If $\gamma_B(C) = 0$, then no element of the universe U can be classified to classes of U/C using attributes B. Thus, the measure $\gamma_B(C)$ can be understood as a degree of dependency between B and C. As a measure of the significance of an attribute $b \in B$ with respect to the classification U/C, we use the quantity

$$\gamma_B(C) - \gamma_{B-b}(C)$$

3. Knowledge Representation

The signal processing routines produce a set of information such as spectrum, pitch, zero crossings, total energy, energy in a low-frequency band, energy in a mid-frequency band, energy in a high-frequency band and etc., which is used by the feature extraction algorithm.

Let U be a universe set of alphadigit vocabularies being considered and A be the set of all attributes functions, each element a_i of which represents one of phonetic features mentioned above. We want to find the most flexible ranges of attributes such that IND (A) become the diagonal $\{ (x,x) | x \in U \}$, which will enable us to make a program to perform fine phonetic distinctions. The condition that $A = \Delta(U)$ must be maintained during manipulating the ranges of attributes to get a complete classification of U.

4. Classification Let us start with $K = (U, A)$, in which U is a fixed set of alphadigit vocabularies and A is a set of phonetic attributes. Choose an attribute function a_1 from A so that U can be classified with least confusion. We can adapt the range of attribute value set V_{a_1}, if necessary, to get better classification U/a_1. We compute the significancy, $\gamma_{A-a_1}(a_1)-\gamma_{A-\{a_1,a_i\}}(a_1)$ of each attribute $a_i \in A$ with respect to the classification U/a_1. Now, choose an attribute a_2 from $A-a_1$ and modify the attribute value set V_{a_2} so that the classification $U/\{a_1, a_2\}$ can be obtained with least confusion and a_2 is of the largest significancy. We continue this process until we get IND$\{a_1, \ldots, a_n\} = \Delta(U)$. If $\{a_1, \ldots, a_n\} \neq A$, we can modify the attribute functions so that each classification U/a ($a \in A$) is done with less confusion, more of elements of A are employed, and the final classification in this process becomes discrete. Of course, the attributes used in this work form the core of A. The more independent attributes are used in this process, the better classification algorithm is obtained.

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