一、中文摘要

個人無線通訊在通訊產業是一快速成長的領域，由於製造技術進步, 導致縮短產品的生命週期及預期上市時間。顧客期望以較低的價格購買功能較多的產品。在手機製程中, 無線頻率(Radio Frequency; RF)功能測試程序相較於其他製造程序需要較多的操作時間。因此製造商需要有效的方法，在 RF 功能檢測品質不變下，減少 RF 測試項目、縮減檢測時間。變數精準粗略集(Variable Precision Rough Sets; VPRS)是資料探勘的重要工具之一, 目前已被廣泛應用於知識獲取。本研究利用 VPRS 減少手機製程中 RF 功能測試的項目，實驗結果顯示雖然測試項目顯著減少, 但利用保留下的測試項目所構成的新測試程序，其檢測準確率非常接近原測試程序。此外，和決策樹方法比較，VPRS 也有較佳的檢測績效。

關鍵詞：資料探勘，無線頻率功能測試，變數精準粗略集，決策樹，手機

ABSTRACT

Personal wireless communication is one of the fastest growing fields in the communications industry. The technology employed by mobile telecommunications is rapidly growing with shorter product life cycles, a shortening of time to market expectations, and a higher customer expectation of more capability for less cost. In mobile phone manufacturing, the radio frequency (RF) functional test process needs more operation time than other processes. Manufacturers require an effective method to reduce the RF test items so that the inspection time can decrease, but still the quality of the RF functional test must be maintained. The Variable Precision Rough Sets (VPRS) model is a powerful tool for data mining, as it has been widely applied to acquire knowledge. In this study the VPRS model is employed to reduce the RF test items in mobile phone manufacturing. Implementation results show that the test items have been significantly reduced. By using these remaining test items, the inspection accuracy is very close to that of the original test procedure. In addition, VPRS demonstrates a better performance than that of the decision tree approach.

Keywords: data mining, RF functional test, VPRS, decision tree, mobile phone.

二、緣由與目的

Personal wireless communication is one of the fastest growing fields in the communications industry. The technology employed by mobile telecommunications is advancing rapidly with shorter product life cycles. In recent years, dual band (GSM/DCS) mobile phone users have been steadily increasing. Furthermore, the diffusion of mobile technology is likely to persist well into this decade. Therefore, mobile phone manufacturers require an effective method to reduce the mobile phone manufacturing time in advance of further market demand.

The global system mobile (GSM) and digital communication system (DCS) are based on different techniques, involving communication methods such as time division multiplex access and discontinuous transmission and power control strategies. The dual band mobile phone manufacturing procedure is shown in Figure 1. From Figure 1, we know that a radio frequency (RF) functional test needs more operation time than other manufacturing processes. The RF test aims to inspect if the mobile phone receive/transmit signal satisfies the enabled transmission interval (ETI) protocol on different channels and power levels. In order to ensure the quality of communication of mobile phones, the manufacturers usually add extra inspection items, such as several different frequency channels and power levels, resulting in inspection time being increased and the test procedure becoming a bottleneck.

The growing volume of information poses interesting challenges and calls for tools that discover properties of data. Data mining has emerged as a discipline that contributes tools for data analysis and the discovery of new knowledge (Kusiak, 2001). The Variable Precision Rough Sets (VPRS) model was introduced by Ziarko (1993) and is an extension of the Rough Set Theory (RST), which is a powerful tool for data mining, as it has been widely applied to acquire knowledge. The reducts generated by the rough sets approach are employed to reduce redundant attributes as well as redundant objects from the decision table. The reducts contain less “noisy” data and provide a decision table that can yield a substantially lower misclassification rate (Hashemi, et al. 1998).

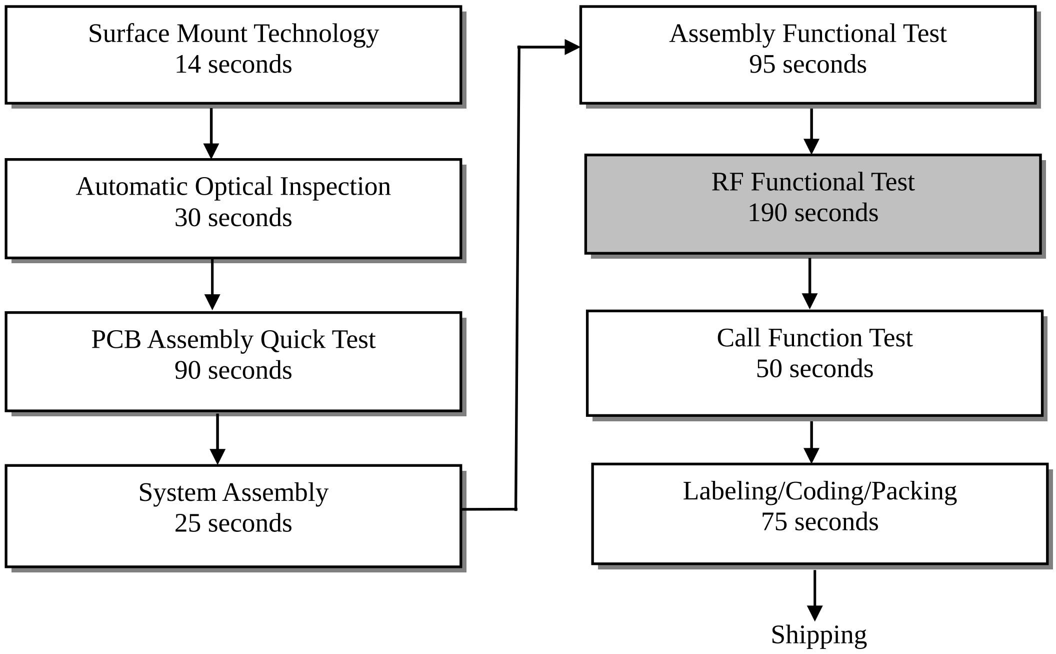

Figure 1. A Manufacturing Process of a Mobile Phone

In this study we utilize the VPRS model for a mobile phone test procedure. In the VPRS model, the extended Chi2 algorithm is used to discretize the continuous attributes, and a β-reduct selection method is used to determine the required attributes. Compared to the decision tree approach, empirical results show promise for the VPRS model to reduce the redundant test items.

Rough sets (RS) as a mathematical methodology for data analysis were introduced by Pawlak (Pawlak, 1991). They provide a powerful tool for data analysis and knowledge discovery from imprecise and ambiguous data. The RS methodology is based on the premise that lowering the degree of precision in the data makes the data pattern more visible. The RS approach can be considered as a formal framework for discovering patterns from imperfect data. The results of RS approach are presented in the form of classification or decision rules derived from given data sets.

RS operates on what may be described as a knowledge representation system or information system. An information system (s) is shown as :

$$S = (U, A)$$

where U is a finite set of objects $(U = \{x_1, x_2, ..., x_n\})$;

A is the set of attributes (condition attributes, decision attributes).

Each attribute $a \in A$ defines an information function $f_a : U \rightarrow V_a$ where V_a is the set of values of a, called the domain of attribute a.

If R is an equivalence relation over U, then by U/R we mean the family of all equivalence classes of R (or classification of U) referred to as categories or concepts of R and $[x]_R$ denotes a category in R containing an element $x \in U$.

For every set of attributes $B \subseteq A$, an indiscernibility relation $Ind(B)$ is defined as: two objects x_i and x_j are indiscernible by the set of attributes B in A, if $b(x_i) = b(x_j)$, for every $b \subset B$.

lower and upper approximations

The RS theory to data analysis hinges on two basic concepts, namely the lower and upper approximations of a dataset. The lower and the upper approximations can also be presented in an equivalent form as shown below:

The lower approximation of the set $X \subseteq U$ and $B \subseteq A$:

$$\underline{B}(X) = \{x_i \in U \mid [x_i]_{Ind(B)} \subset X\}.$$

The upper approximation of the set $X \subseteq U$ and $X \subseteq A$:

$$\overline{B}(X) = \left\{x_i \in U \mid [x_i]_{Ind(B)} \cap X \neq \phi\right\}.$$

The variable precision rough sets (VPRS) model is an extension of the original rough sets model (Ziarko, 2001), which was proposed to analyze and identify data patterns that represent statistical trends rather than functional trends. VPRS deals with partial classification by introducing a precision parameter β. The β value represents a bound on the conditional probability of a proportion of objects in a condition class that are classified to the same decision class.

VPRS operates on what may be described as a knowledge representation system or information system. An information system (*S*) consisting of four parts is shown as:

$$S = (U, A, V, f),$$

where U is a non-empty set of objects;

A is the collection of objects; we have $A = C \bigcup D$ and $C \bigcap D = \phi$, where C is a non-empty set of condition attributes, and D is a non-empty set of decision attributes;

V is the union of attribute domains, i.e., $V = \bigcup_{a \in A} V_a$, where V_a is a finite attribute domain and the elements of V_a are called values of attribute *a*;

F is an information function such that $f(u_i, a) \in V_a$ for every $a \in A$ and $u_i \in U$.

Every object that belongs to U is associated with a set of values corresponding to the condition attributes C and decision attributes D.

β-lower and β-upper approximations

Suppose that information system *S = (U, A, V, f)*, with each subset $Z \subseteq U$ and whereby an equivalence relation R, referred to as an indiscernibility relation, corresponds to a partitioning of *U* into a collection of equivalence classes $R^* = \{E_1, E_2, ..., E_n\}$. We will assume that all sets under consideration are finite and non-empty (Ziarko, 2002). The variable precision rough sets approach to data analysis hinges on two basic concepts, namely the β-lower and the β-upper approximations of a set. The β-lower and the β-upper approximations can also be presented in an equivalent form as shown below:

The β -lower approximation of the set $Z \subseteq U$ and $P \subseteq C$:

$$\underline{C}_\beta(D) = \bigcup_{1-P_r(Z|x_i)\le\beta} \{x_i \in E(P)\}.$$

The β -upper approximation of the set $Z \subseteq U$ and $P \subseteq C$:

$$\overline{C}_\beta(D) = \bigcup_{1-P_r(Z|x_i)<1-\beta} \{x_i \in E(P)\}.$$

where

$E(\bullet)$ denotes a set of equivalence classes (in the above definitions, they are condition classes based on a subset of attributes P);

$$p_r(Z \mid x_i) = \frac{Card(Z \bigcap x_i)}{Card(x_i)}.$$

Quality of classification

Based on Ziarko (1993), the measure of quality of classification for the VPRS model is defined as:

$$\gamma(P, D, \beta) = \frac{card(\bigcup_{1-p_r(Z|x_i)\le\beta}\{x_i \in E(P)\})}{card(U)}, \tag{1}$$

where $Z \subset E(D)$ and $P \subseteq C$, for a specified value of β. The value $\gamma(P, D, \beta)$ measures the proportion of objects in the universe (U) for which a classification (based on decision attributes D) is possible at the specified value of β.

Core and β-reducts

If the set of attributes is dependent, then we are interested in finding all possible minimal subsets of the attribute, which leads to the same number of elementary sets as the whole attributes (β-reduct), and in finding the set of all indispensable attributes (core). The β-reduct is the essential part of the information system, which can differentiate all discernable objects by the original information system. The core is the common part of all β-reducts.

A β-reduct of the set of condition attributes P $(P \subseteq C)$ with respect to a set of decision attributes D is a subset $RED(P, D, \beta)$ of P which satisfies the following two criteria (Ziarko, 1993):

(1) $\gamma(P, D, \beta) = \gamma(RED(P, D, \beta), D, \beta)$;

(2) no attributes can be eliminated from $RED(P, D, \beta)$ without affecting the requirement (1).

To compute reducts and core, the discernibility matrix is used. Let the information system $S = (U, A)$ with $U = \{x_1, x_2, ..., x_n\}$. We use a discernibility matrix of S, denoted as $M(S)$, which has the dimension $n \times n$, where

n denotes the number of elementary sets, defined as

$(c_{ij}) = \{a \in A \mid a(x_i) \neq a(x_j), 1 \leq i, j \leq n\}$ Thus, entry c_{ij} is the set of all attributes which discern objects x_i and x_j.

The core can be defined as the set of all single element entries of the discernibility matrix (Pawlak, 1991), i.e.

$$core(A) = \{a \in A \mid c_{ij} = (a),\ for\ some\ i, j\}.$$

The discernibility matrix can be used to find the minimal subset(s) of attributes, which leads to the same partition of the data as the whole set of attributes *A*. To do this, we have to construct the discernibility function $f(A)$. This is a Boolean function and is constructed in the following way: to each attribute from the set of attributes, which discern two elementary sets, (e.g., $\{a_1, a_2, a_3, a_4\}$), we assign a Boolean variable '*a*', and the resulting Boolean function attains the form $(a_1 + a_2 + a_3 + a_4)$, or it can be presented as $(a_1 \vee a_2 \vee a_3 \vee a_4)$. If the set of attributes is empty, then we assign to it the Boolean constant 1 (Walczak, et al. 1999).

Rules Extraction

The procedure for generating decision rules from an information system has two main steps as follows:

Step 1: Selection of the best minimal set of attributes (i.e. β-reduct selection).

Step 2: Simplification of the information system can be achieved by dropping certain values of attributes that are unnecessary for the information system.

The procedure of the VPRS model has five steps as follows:

Step 1: Discretization of continuous attributes.

Step 2: Find the full set of β-reduct (i.e., attributes selection).

Step 3: Elimination of duplicate rows.

Step 4: Elimination of superfluous values of attributes.

Step 5: Rules extraction.

The RST is a special case of VPRS model.

The Discretization Algorithm

Deriving classification rules is an important task in data mining. As such, discretization is an effective technique in dealing with continuous attributes for rule generating. Many classification algorithms require that the training data contain only discrete attributes, and some would work better on discretized or binarized data (Li, et al. 2002; Kerber, 1992). However, for these algorithms, discretizing continuous attributes is a first step for deriving classification rules. The Variable Precision Rough Sets (VPRS) model is one example.

There are three different axes by which discertization methods can be classified: local versus global, supervised versus unsupervised, and static versus dynamic (Dougherty, et al. 1995). Local methods, such as C4.5 (Quinlan, 1993), produce partitions that are applied to localized regions of the instance space. By contrast, the global discertization method uses the entire instance space to discretize. Several discretization methods, such as equal width interval and equal frequency interval methods, do not utilize instance class labels in the discretization process. These methods are called unsupervised methods. Conversely, discretization methods that utilize the class labels are referred to as supervised methods.

Many discretization methods require some parameter, m, indicating the maximum number of intervals to produce in discretizing an attribute. Static methods, such as entropy-based partitioning, perform one discretization pass of the data for each attribute and determine the value of m for each attribute independent of the other attributes. Dynamic methods conduct a search through the space of possible m values for all attributes simultaneously, thereby capturing interdependencies in attribute discretization.

The ChiMerge algorithm introduced by Kerber (1992) is a supervised global discretization method. The user has to provide several parameters such as the significance level α, and the maximal intervals and minimal intervals during the application of this algorithm. ChiMerge requires α to be specified. Nevertheless, too big or too small a α will over-discretize or under-discretize an attribute.

An effective discretization algorithm, called extended Chi2 algorithm, proposed by Su and Hsu (2005) is employed. This algorithm utilizes ChiMerge algorithm as a basis and determines the misclassification rate of the VPRS based on the least upper bound $\xi(C, D)$ of the data set, where C is the equivalence relation set, D is the decision set, and

$C^* = \{E_1, E_2, ..., E_n\}$ is the equivalence classes. According to Ziarko (1993), for the specified majority requirement, the admissible misclassification rate (β) must be within the range $0 \le \beta < 0.5$. Thus, the following equality is used for calculating the least upper bound of the data set.

$$\xi(C, D) = \max(m_1, m_2)\,, \qquad (2)$$

where

$$m_1 = 1 - \min\{c(E,D) \mid E \in C^* \text{ and } 0.5 < c(E,D)\}$$

$$m_2 = \max\{c(E,D) \mid E \in C^* \text{ and } c(E,D) < 0.5\}\,.$$

The inconsistency checking of the extended Chi2 algorithm is replaced by the least upper bound ξ after each step of discretization $(\xi_{discretized} < \xi_{original})$. By doing this, the inconsistency rate is utilized as the termination criterion. Moreover, it considers the effect of variance in the two merging intervals, whereby the adjacent intervals have a maximal normalize difference $(= difference / \sqrt{2 * v})$ that should be merged.

Selection of β-reducts

In the VPRS model, the precision parameter β can be considered as a misclassification rate; usually, it is defined in the domain $[0.0, 0.5)$ (Ziarko, 1993). Whereas the VPRS model has no formal historical background of having empirical evidence to support any particular method of β-reducts' selection (Beynon, 2002), VPRS-related research studies do not focus in detail on the choice of the precision parameter (β) value. Ziarko (1993) proposed the β value to be specified by the decision maker. Beynon (2000) offered two methods of selecting a β-reduct without such a known β value. Beynon (2001) suggested the allowable β value range to be an interval, where the quality of classification may be known prior to determining the β value range.

The β value of the VPRS model will control the choice of β-reducts. Ziarko (1993) defined the measure of the relative degree of misclassification of the set X with respect to Y as:

$$c(X, Y) = \begin{cases} 1 - \dfrac{card(X \cap Y)}{card(X)} & \text{if } card(X) > 0 \\ 0 & \text{if } card(X) = 0 \end{cases}$$

Here, card denotes set cardinality.

Let X and Y be non-empty subsets of U. The measure of relative misclassification can define the inclusion relationship between X and Y without explicitly using a general quantifier:

$$Y \supseteq X \Leftrightarrow c(X, Y) = 0.$$

The majority inclusion relation is defined as:

$$Y \overset{\beta}{\supseteq} X \Leftrightarrow c(X, Y) \le \beta\,.$$

The above definition covers the entire family of β-majority relations.

The β-reducts can be found by using the following steps:

Step 1: Find the candidates of β-reducts using precision parameter (β) based on (2).

Step 2: For each candidate of β-reducts (subset P), calculate the quality of classification based on (1).

Step 3: Remove redundant attributes.

Step 4: Find the β-reducts. The subset $X(X \subseteq P)$, when its quality of classification is the same as that of a full set, is a β-reduct.

三、結果與討論

For the purpose of an empirical implementation, we collected data from a mobile phone manufacturer located in Taoyuan, Taiwan. Each RF functional test includes nine test items and they are: the power versus time (PVT; symbol: A), the power level (TXP; symbol: B), the phase error and frequency error (PEFR; symbol: C), the bit error rate (BER-20; symbol: D), the bit error rate (BER-(-102); symbol: E), the ORFS-spectrum due to switching transient (ORFS_SW; symbol: F), the ORFS-spectrum due to modulation (ORFS_MO; symbol: G), the Rx level report accuracy (RXP_Lev_Err; symbol: H), and the Rx level report quality (RXP_QUALITY; symbol: I). Each test item according to different channels and power levels has separated several test attributes. Each test attributes' form is to be represented as: test item-channel-power level, which has a total of 62 test attributes including 27 continuous value test attributes and 35 discrete value test attributes.

In this study 168 objects are collected, and these objects are separated into a training set that includes 112 objects (84 objects that passed; 28 objects that failed) and a test set that includes 56 objects (28 objects that passed; 14 objects that failed).

Since the VPRS model needs the data in a categorical form, the continuous attributes must be discretized before the VPRS analysis is performed. By using extended Chi2 algorithm, the number of continuous attributes is reduced from 27 to 20. The results are listed in Table 1. Therefore, the RF function test has 55 test attributes (35 discrete attributes and 20 discretization attributes) for further study.

In this study the objects have been classified into one of two categories, 0 (passed) and 1 (failed). By formula (2), the precision parameter (β) value is equal to 0. In this case, the VPRS model is reduced to RS model. According to the process of finding β-reducts in section 3.2, the full set of β-reducts associated with the information system is given in Table 2. Since the β-reduct {*B*-114-5, *E*-114-5, *H*-965-(-102), *B*-522-0, *B*-688-15} has the least number of attributes and the least number of combinations of values of its attributes, it is selected for further study. The $M(S)$-information system for this β-reduct will be: {*B*-114-5, *E*-114-5, *H*-965-(-102), *B*-522-0, *B*-688-15}. That is to say, the number of test attributes is reduced from 55 to 5. Based on the $M(S)$-discernibility matrix constructed by the $M(S)$- information system, the superfluous values of the test attributes can be eliminated and the extracted rules are listed in Table 3. We can see that the objects of the test set at rule 3, rule 9, rule 10, rule 11, rule 12, and rule 16 are null, while rule 6, rule 13, rule 14, and rule 15 show only one object in the test set. Since these rules are not a matter for the judgment of the product, they are deleted. The final extraction rules are listed in Table 4. From Table 4. we know that the accuracy of the extraction rules in the test set is 98.21% (55/56).

Table 1. Condition attributes' ranges for extended Chi2 algorithm

	Range '1'	Range '2'	Range '3'	Range '4'	Range '5'	Range '6'	Range '7'	Range '8'	Range '9'	Range '10'	Range '11'	Range '12'	Range '13'
B-10-5	30.62 ~31.92	31.98 ~32.11	32.12 ~32.13	32.14 ~32.36	32.37 ~32.45	—	—	—	—	—	—	—	—
B-114-5	30.21 ~31.33	31.46 ~31.67	31.68 ~31.82	31.83	31.84 ~31.85	31.86 ~31.87	31.88 ~31.89	31.90	31.91 ~32.11	32.13 ~32.17	—	—	—
B-522-0	23.49 ~25.58	28.39 ~28.44	28.45	28.46 ~28.62	28.63 ~28.84	28.85	28.86 ~28.97	28.99 ~29.01	29.02 ~29.07	29.08 ~29.09	29.10 ~29.13	29.14 ~29.35	29.37
B-688-15	-3.01 ~-0.63	0.69 ~0.94	0.95	0.96 ~1.15	1.16 ~1.19	1.21 ~1.32	—	—	—	—	—	—	—
B-688-0	23.45 ~26.27	28.95 ~29.07	29.08 ~29.20	—	—	—	—	—	—	—	—	—	—
B-688-3	19.37 ~23.57	23.68 ~23.83	23.84 ~23.89	23.90 ~24.06	—	—	—	—	—	—	—	—	—
B-688-7	11.34 ~14.74	15.11 ~15.50	15.51	15.52 ~15.70	—	—	—	—	—	—	—	—	—
B-72-11	19.35 ~20.54	20.55 ~21.07	—	—	—	—	—	—	—	—	—	—	—
B-72-19	3.31 ~5.24	5.28 ~5.33	5.34 ~5.35	5.36 ~5.64	—	—	—	—	—	—	—	—	—
B-72-5	30.25 ~31.61	31.62	31.63 ~31.68	31.69 ~31.74	31.75 ~31.82	—	—	—	—	—	—	—	—
B-72-7	27.51 ~28.89	28.91 ~28.98	28.99 ~29.36	—	—	—	—	—	—	—	—	—	—
B-875-0	25.98 ~27.98	28.06 ~28.28	28.29 ~28.64	28.65 ~28.66	28.67 ~28.69	28.72	28.73 ~28.87	28.91 ~29.08					
B-965-5	30.70 ~32.46	32.48 ~32.99	33.00 ~33.26	—	—	—	—	—	—	—	—	—	—
E-10-5	0.00000 ~0.07284	0.11655 ~3.07401	—	—	—	—	—	—	—	—	—	—	—
E-114-5	0.00000 ~0.04371	0.05828 ~0.07284	0.08741 ~3.74300	—	—	—	—	—	—	—	—	—	—
E-522-0	0.07284	0.10198 ~0.30594	0.32051	0.33508 ~0.49534	0.99068 ~3.88986	—	—	—	—	—	—	—	—
E-688-0	0.00000 ~0.07284	0.08741 ~0.21853	0.32051 ~3.24883	—	—	—	—	—	—	—	—	—	—
E-72-5	0.00000 ~0.0291	0.0437	0.0583 ~0.1020	0.1603 ~3.3217	—	—	—	—	—	—	—	—	—
E-875-0	0.08741 ~0.58275	1.15093 ~3.77331	—	—	—	—	—	—	—	—	—	—	—
E-965-5	0.00000 ~0.04371	0.05828 ~0.17483	0.43706 ~3.52564	—	—	—	—	—	—	—	—	—	—

Table 2. β -reducts associated with the information system

β -reduct			
1	{B-114-5, H-114--102, B-522-0, I-522-(-102), B-688-15}	15	{E-72-5, B-114-5, H-114-(-102), B-522-0, I-522-(-102), H-875-(-102)}
2	{B-72-7, B-114-5, H-114-(-102), B-522-0, B-688-15}	16	{B-114-5, H-114-(-102), B-522-0, I-522-(-102), H-875-(-102), I-875-(-102)}
3	{B-10-5, B-114-5, H-114-(-102), B-522-0, B-688-3}	17	{B-72-7, B-114-5, H-114-(-102), B-522-0, E-688-0, H-875-(-102)}
4	{B-114-, H-114-(-102), B-522-0, E-522-0, B-688-15}	18	{H-10-(-102), B-72-7, B-114-5, B-522-0, E-688-0, H-875-(-102)}
5	{B-72-19, B-114-5, H-114-(-102), B-522-0, B-875-0}	19	{H-10-(-102), B-72-5, E-72-5, B-114-5, B-522-0, H-875-(-102)}
6	{B-114-5, E-114-5, H-965-(-102), B-522-0, B-688-15}	20	{H-10-(-102), B-72-5, B-114-5, B-522-0, H-875-(-102), I-875-(-102)}
7	{B-114-5, H-114-(-102), B-522-0, I-522-(-102), B-688-3, I-875-(-102)}	21	{H-10-(-102), B-72-5, B-114-5, B-522-0, H-688-(-102), I-875-(-102)}
8	{B-72-5, E-72-5, B-114-5, H-114-(-102), B-522-0, G-522-0}	22	{B-72-5, B-114-5, H-114-(-102), B-522-0, G-522-0, B-875-0}
9	{B-72-7, B-114-5, H-965-(-102), B-522-0, E-688-0, I-875-(-102)}	23	{H-10-(-102), B-72-19, B-114-5, C-965-5, B-522-0, B-688-15}
10	{H-10-(-102), B-72-5, E-72-5, B-114-5, H-114-(-102), B-522-0}	24	{H-10-(-102), E-72-5, B-114-5, B-522-0, I-522-(-102), F-875-0}
11	{B-72-5, E-72-5, B-114-5, H-114-(-102), B-522-0, B-688-0}	25	{H-10-(-102), C-72-5, B-114-5, E-114-5, B-522-0, I-522-(-102)}
12	{B-72-5, E-72-5, B-114-5, H-114-(-102), B-522-0, I-522-(-102)}	26	{H-10-(-102), G-72-5, B-114-5, E-114-5, B-522-0, I-522-(-102)}
13	{B-72-5, E-72-5, B-114-5, H-114-(-102), B-522-0, G-688-0}	27	{H-10-(-102), B-72-7, B-114-5, E-965-5, B-522-0, B-688-15}
14	{B-114-5, H-114-(-102), B-522-0, I-522-(-102), B-875-0, G-875-0}		

Table 3. Results of rule extraction (VPRS)

Method	Extraction Rules	Accuracy	
		Training Set	Test Set
VPRS	1. If 32.13≦B-114-5<31.46, then one has failed.	100% (5/5)	100% (4/4)
	2. If 31.46≦B-114-5≦31.82, 0≦E-114-50.07284, H-965-(-102) ≦7 and 28.46≦ B-522-0≦28.97, then one is passed.	95.12% (39/41)	95.83% (23/24)
	3. If H-965-(-102), then one has failed.	100% (5/5)	—
	4. If 31.68≦B-114-5≦31.82, 0≦E-114-5≦0.04731, H-965-(-102)=1 and 0.69≦B-688-15≦1.15, then one is passed.	100% (3/3)	100% (2/2)
	5. If 31.91≦B-114-5≦32.11, H-965-(-102) ≦1 and 0.69≦B-688-15≦1.15, then one is passed.	100% (20/20)	100% (6/6)
	6. If 31.91≦B-114-5≦32.11, H-965-(-102) =1 and 1.16≦B-688-15≦1.19, then one has failed.	100% (1/1)	100% (1/1)
	7. If 0.08741≦E-114-5, then one has failed.	100% (6/6)	100% (9/9)
	8. If 31.84≦B-114-5≦31.89, 28.46≦B522-0≦29.07 and 0.69≦B-688-15≦1.19, then one is passed.	100% (9/9)	100% (7/7)
	9. If 31.84≦B-114-5≦31.87, 28.86≦B-522-0 and 1.21≦B-688-15, then one has failed.	100% (2/2)	—
	10. If B-688-15=0.95, then one has failed.	100% (2/2)	—
	11. If 31.83≦B-114-5≦31.89 and 0.69≦B-688-15≦0.94, then one is passed.	100% (5/5)	—
	12. If 31.68≦B-114-5≦31.82, H965-(-102) ≦1 and 1.21≦B-688-15, then one is passed.	100% (2/2)	—
	13. If 31.88≦B-114-5 and H-965-(-102) ≦1 and 1.21≦B-688-15, then one is passed.	100% (2/2)	100% (1/1)
	14. If 0≦E-114-5≦0.07284, H-965-(-102) ≦2 and B-522-0≧28.63, then one has failed.	100% (4/4)	100% (1/1)

Table 3 (continued). Results of rule extraction (VPRS)

	15. If B-114-5≧31.90, 0.05828≦E-114-5≦0.07284, H965-(-102)=1 and 0.69≦B-688-15≦0.94, then one is passed.	100% (3/3)	100% (1/1)
	16. If 23.49≦B-522-0≦25.58 and B-688-15≦0.68, then one has failed.	100% (1/1)	—

Notes: 1. (/) indicates (number of correct instances/number of total instances).
2. "—"indicates the object in the set is null.

Table 4. Final results of rule extraction (VPRS)

Method	Extraction Rules	Accuracy	
		Training Set	Test Set
VPRS	1. If 32.13≦B-114-5<31.46, then one has failed.	100% (5/5)	100% (4/4)
	2. If 31.46≦B-114-5≦31.82, 0≦E-114-50.07284, H-965-(-102) ≦7 and 28.46≦ B-522-0≦28.97, then one is passed.	95.12% (39/41)	95.83% (23/24)
	3. If 31.68≦B-114-5≦31.82, 0≦E-114-5≦0.04731, H-965-(-102)=1 and 0.69≦B-688-15≦1.15, then one is passed.	100% (3/3)	100% (2/2)
	4. If 31.91≦B-114-5≦32.11, H-965-(-102) ≦1 and 0.69≦B-688-15≦1.15, then one is passed.	100% (20/20)	100% (6/6)
	5. If 0.08741≦E-114-5, then one has failed.	100% (6/6)	100% (9/9)
	6. If 31.84≦B-114-5≦31.89, 28.46≦B522-0≦29.07 and 0.69≦B-688-15≦1.19, then one is passed.	100% (9/9)	100% (7/7)

Notes: (/) indicates (number of correct objects/ number of total objects).

Using the Decision Tree Approach

In this section the See 5 software package is used to perform the computation. The parameters of See5 utilize its default setting. The tree structure is shown in Figure 2., from which we know that *C*-965-5, *B*-688-3, *H*-965-(-102), *B*-688-0, *E*-114-5, and *G*-114-5 are important attributes of the RF functional test. The number of RF functional test attributes will be reduced from 55 to 6. The extracted rules are listed in Table 5. We know that the objects of the test set at rule 3 and rule 7 are null, while rule 2 and rule 4 show only one object in the test set. Since these rules are not a matter for the judgment of the product, they are deleted. The final extraction rules are listed in Table 6. In the test set, three objects do not match any of the rules and the accuracy of the extraction rules is 94.64% (53/56).

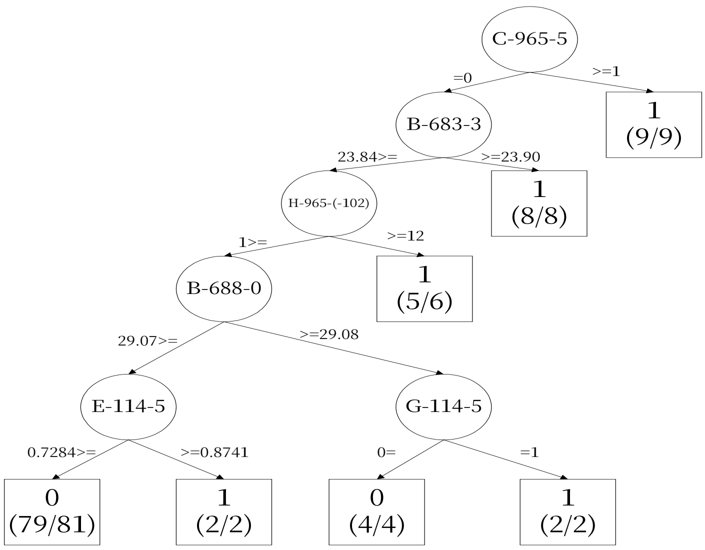

Figure 2. Tree structure of the information system

Table 5. Results of rule extraction (See 5 software)

Method	Extraction Rules	Accuracy	
		Training Set	Test Set
See 5	1. If C-965-5≧1, then one has failed.	100% (9/9)	100% (3/3)
	2. C-965-5 and B-688-3≧23.90, then one has failed.	100% (8/8)	100%(1/1)
	3. If C-965-5=0, B-688-3≦23.84 and H-965-(-102)≧12, then one has failed.	85.71%(6/7)	—
	4. If C-965-5=0, B-688-3≦23.84, H-965-(-102)≦1, B-688-0 ≧29.08 and G-114-5=0, then one is passed.	100% (4/4)	100% (1/1)
	5. If C-965-5=0, B-688-3≦23.84, H-965-(-102)≦1, B-688-0 ≧29.08 and G-114-5=1, then one has failed.	100% (2/2)	100% (8/8)
	6. If C-965-5=0, B-688-3≦23.84, H-965-(-102)≦1, B-688-0 ≦29.07 and E-114-5≧0.8741, then one has failed.	97.60 % (81/83)	100% (40/40)
	7. If C-965-5=0, B-688-3≦23.84, H-965-(-102)≦1, B-688-0 ≦29.07 and E-114-5≦0.8741, then one is passed.	100% (2/2)	—

Notes: 1. (/) indicates (number of correct instances/number of total instances).
2. "— " indicates that the object in the set is null.
3. In the test set, three objects do not match any of the rules.

Table 6. Final results of rule extraction (See 5 software)

Method	Extraction Rules	Accuracy	
		Training Set	Test Set
See 5	1. If C-965-5≧1, then one has failed.	100% (9/9)	100% (3/3)
	2. If C-965-5=0, B-688-3≦23.84, H-965-(-102)≦1, B-688-0 ≧29.08 and G-114-5=1, then one has failed.	100% (2/2)	100% (8/8)
	3. If C-965-5=0, B-688-3≦23.84, H-965-(-102)≦1, B-688-0 ≦29.07 and E-114-5≧0.8741, then one has failed.	97.60 % (81/83)	100% (40/40)

Notes: 1. (/) indicates (number of correct instances/number of total instances).
2. In the test set, three objects do not match any of the rules.

A comparison

The effectiveness of the VPRS model is conducted at the test line in the case company. Assume that the inspection accuracy of the original test procedure is 100%. According to Table 7., the implementation results under normal production over six weeks confirm that the overall inspection accuracies for the VPRS model and decision tree approach are 99.75% and 99.61%, respectively. This fact shows that the quality of the RF functional test will be not affected, when some unimportant test items are removed by using the VPRS model or the decision tree approach. The VPRS model outperforms the decision approach in terms of inspection accuracy. Moreover, the test time of the original RF test procedure (62 test attributes) is 190 seconds, while the VPRS model (5 test attributes) is 34.5 seconds and the decision tree approach (6 test attributes) is 43.2 seconds. This leads to the number of RF test machines is reduced from 8 to 4, which saving equipment cost 6 million NT dollars (each machine cost is 1.5 million NT dollars) from implementation the VPRS model in RF test procedure. Those extracted rules that form Table 4. (or Table 6.) will help a company to construct a knowledge base to train new engineers.

Table 7. A comparison of the VPRS model and decision tree

Week	VPRS		Decision Tree (See 5 software)	
	Pass instances accuracy (%)	Fail instances accuracy (%)	Pass instances accuracy (%)	Fail instances accuracy (%)
1	100% (639/639)	75% (6/8)	100% (639/639)	75% (6/8)
2	100% (1240/1240)	86.36% (19/22)	100% (1240/1240)	72.72% (16/22)
3	100% (316/316)	100% (2/2)	100% (316/316)	100% (2/2)
4	100% (108/108)	100% (2/2)	100% (108/108)	100% (2/2)
5	100% (198/198)	75% (3/4)	100% (198/198)	100% (4/4)
6	100% (305/305)	80% (4/5)	100% (305/305)	40% (2/5)
Overall	100% (2806/2806)	83.72% (36/43)	100% (2806/2806)	74.42% (32/43)
	99.75% (2842/2849)		99.61% (2838/2849)	

Notes: (/) indicates (number of correct instances/number of total instances).

四、計劃成果自評

The technology employed by mobile telecommunications is rapidly evolving with shorter product life cycles and a shortening of the time to market expectations, such that mobile phone manufacturers require an effective method to reduce the operation time to satisfy market expectations. Data mining is an emerging area of computational intelligence that offers new theories, techniques, and tools for processing large volumes of data. The VPRS is a powerful tool of data mining to reduce the redundant attributes and extract useful rules.

This study employed the VPRS model to reduce the redundant RF functional test items in mobile phone manufacturing. We utilized the extended Chi2 algorithm to discrete continuous attributes, and chose a suitable method to select the β -reducts. Implementation results show that the test items have been significantly reduced. By using these remaining test items, the inspection accuracy is very close to that of the original test procedure. VPRS also demonstrates a better performance than that of the decision tree approach. Moreover, the operation time of the RF functional test procedure by using the VPRS model is significantly less than that of the decision tree approach and the original RF functional test procedure. By using the VPRS model, the throughput will increase and the time to market will be reduced. In addition, the extracted rules constructed in this study can be used to interpret the relationship between condition and decision attributes and help companies to construct their own knowledge base for training new engineers.

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