rough set, biomarker, IgA, POMS, stress

Yasuo KUDO[*], Shusaku NOMURA[**]

A CRITERION FOR ATTRIBUTES IN ROUGH SET THEORY AND ITS APPLICATION TO ANALYSIS ON THE RELATION BETWEEN HUMAN PSYCHOLOGICAL MOOD STATE AND THE IMMUNE FUNCTION

Recent behavioural medicine studies have revealed that the human secretory substances change according to his/her mental states. Especially, those substances transiently get increase (or decrease) against the short-term experimental stressors. However, the relation with rather longer stressor, or daily stressor, has not yet well understood or reported discrepant results. One possible reason for this discrepancy might be brought from uncertainty of the psychological evaluation, which is the score of subjective questionnaire. We then introduced an evaluation criterion of attributes based on rough set theory to analyze the relation between the psychological state and a major immune substance. As a result, several items in the questionnaire were extracted as dominant items, while there was still no correlation between them.

1. INTRODUCTION

In this paper, we introduce an evaluation criterion of condition attributes [3] based on rough set theory [5] to extract the relationship between human psychological and physiological states. Recent behavioural medicines and psychophysiological studies have suggested the close relationship between human psychological and physiological states. It suggests the possibility of using changes of human secretion within body as “criteria” of his/her mental states. For example, human secretory IgA shows transient increase by short-term experimental stressor such as arithmetic task [1, 2, 6]. This relatively new field of study has been drastically developed according to the improvement of biochemical analysis techniques such as radioimmunoassay (RIA) and enzyme-liked immune sorbent assay (ELISA). Nowadays, at least a dozen of human secretory substances were considered as candidates of the "biomarker" of human psychological sates [7]. Most of these studies have assessed the change of concentration of the substances in secretory fluid against psychological stressors, and have shown consistent results. So far as against the short-term experimental stressors, these substances in secretory fluid such as blood, urine and saliva are quite useful biomarkers (stress-markers).

On the other hand of these studies on the laboratory stressors, studies investigating the effect of rather long-term stressors or daily stressful experience to these biomarkers have shown discrepant results. In those studies, the relevance between psychological state and physiological state has been evaluated by the correlation analysis between the score of psychological questionnaire and the amount of secretory substance. The correlation analysis is the one-to-one factorial evaluation method based on linearity between the target factor and the other one. In other words, one can easily imagine that the correlation analysis suggests no result if the target factor such as the change in secretory substance were mediated by several psychological factors, or if the relevance were in the form of non-linearity. Therefore, it can be worth introducing independent analytical methodology. As an attempt of non-linear analysis, we have introduced rough set theory to extract the relevance between the score of psychological questionnaire and the amount of one salivary biomarker by using a newly proposed criterion called the “Degree of Contribution (DoC)” with respect to attribute reduction techniques in rough set theory [4]. Data analysis by rough set theory has no stochastic restriction such as the number of data, linearity and independency of factors. Also, relationship among multiple factors can be analyzed simultaneously. However, computational complexity of calculating DoC of all questions in a questionnaire is NP-hard and therefore questionnaires with many questions are intractable.

In this paper, we then propose a new criterion that is easier to calculate than DoC, and apply to the analysis of the relevance between the score of psychological questionnaire and the amount of one salivary biomarker. In the experiment, we use the ``the profile of mood state" (POMS) as for the questionnaire and the concentration of salivary immunoglobulin A (IgA) as for the biomarker.

2. ROUGH SET

2.1. LOWER AND UPPER APPROXIMATIONS AND RELATIVE REDUCTS IN DECISION TABLES

In rough set data analysis, objects as targets of analysis are illustrated by combination of multiple attributes and those values, and represented by the following decision table:

$$DT = (U, C, d), \tag{1}$$

[*] Muroran Institute of Technology, 27-1 Mizumoto, Muroran 058-8585, Japan
[**] Nagaoka University of Technology, 1603-1 Kamitomioka, Nagaoka 940-2188, Japan

where U is the set of objects, C is the set of condition attributes such that each attribute $a \in C$ is a function $a : U \to V_a$ from U to the set V_a of values of a, and d is a function $d : U \to V_d$ called the decision attribute.

The indiscernibility relation R_B on U with respect to a set $B \subseteq C \cup \{d\}$ is defined by

$$xR_B y \Leftrightarrow a(x) = a(y), \forall a \in B. \tag{2}$$

It is easy to confirm that any indiscernibility relation is an equivalence relation. The equivalence class $[x]_B$ of $x \in U$ by R_B is the set of objects that are not discernible with x even though using all attributes in B. Any indiscernibility relation R_B provides a partition $U/R_B = \{[x]_B \mid x \in U\}$ of U. In particular, the partition $U/R_D = \{D_1, \cdots, D_p\}$ provided by the indiscernibility relation R_d with respect to the decision attribute d is called the set of decision classes, and each equivalence class D_i $(1 \le i \le p)$ is called a decision class.

For any decision class D_i, the lower approximation $\underline{B}(D_i)$ and upper approximation $\overline{B}(D_i)$ of D_i with respect to the indiscernibility relation R_B are defined as

$$\underline{B}(D_i) = \{x \in U \mid [x]_B \subseteq D_i\}, \tag{3}$$

$$\overline{B}(D_i) = \{x \in U \mid [x]_B \cap D_i \neq \emptyset\}. \tag{4}$$

A pair $\left(\underline{B}(D_i), \overline{B}(D_i)\right)$ is called a rough set of D_i.

Decision rules describe combination patterns of values between condition attributes and the decision attribute. In this paper, we denote a decision rule constructed from a subset $B \subseteq C$ of condition attribute, the decision attribute d and an object $x \in U$ by $(B, x) \to (d, x)$. Certainty and coverage are well known criteria of decision rules. For any decision rule $(B, x) \to (d, x)$, The value $Cer(\cdot)$ of certainty and the value $Cov(\cdot)$ of coverage of the decision rule are defined by

$$Cer\left((B, x) \to (d, x)\right) = \frac{|[x]_B \cap D_i|}{|[x]_B|}, \tag{5}$$

$$Cov\left((B, x) \to (d, x)\right) = \frac{|[x]_B \cap D_i|}{|D_i|}, \tag{6}$$

where D_i is the decision class such that $x \in D_i$, and $|S|$ is the cardinality of the set S. Certainty represents the degree of correctness and coverage describes the degree of generality of the decision rules, respectively.

Table 1 represents an example of decision tables we uses in this paper, and consists of the following elements: $U = \{s1, \cdots, s8\}$, $C = \{Q.5, Q.10, Q.25, Q.32, Q.40, Q.45, Q.60\}$, and IgA as the decision attribute. IgA provides four decision classes D_i $(1 \le i \le 4)$ such that $D_i = \{x \in U \mid IgA(x) = i\}$. For example, a decision rule $(B, s1) \to (d, s1)$ constructed from $B = \{Q.5, Q.10\}$ and $s1 \in U$ describes the following value patterns among attributes:

$$(Q.5 = 1) \wedge (Q.10 = 3) \to (IgA = 3),$$

and the certainty of this decision rule by (5) is 1.0 and the coverage by (6) is 0.5, respectively.

Table 1. Decision table

	Q.5	Q.10	Q.25	Q.32	Q.40	Q.45	Q.60	IgA
s1	1	3	1	3	1	3	1	3
s2	2	2	1	2	2	3	1	1
s3	3	1	0	2	2	2	2	2
s4	2	1	0	3	3	3	2	1
s5	2	3	2	3	2	3	3	1
s6	1	1	0	0	1	2	2	4
s7	0	1	1	1	0	2	1	3
s8	1	2	2	4	1	0	3	2

2.2. AN EVALUATION CRITERION OF CONDITION ATTRIBUTES

Kudo [3] has proposed an evaluation criterion of condition attributes based on correctness and roughness of partition constructed from a condition attribute with respect to the set of decision classes. For each condition attribute $a \in C$, the criterion is defined by

$$Eval(a) = \frac{1}{2}\left(ACer(a) + ACov(a)\right), \tag{7}$$

where $ACer(B)$ and $ACov(B)$ are the average of certainty and the average of coverage of all decision rules $(a,x) \to (d,x)$ $(\forall x \in U)$ constructed from a, respectively. In this criterion, by combining evaluations of decision rules $(a,x) \to (d,x)$, the value $ACov(B)$ evaluates the correctness of the partition U/R_a constructed from the condition attribute a, and the value $ACov(B)$ evaluates the roughness of the partition, respectively. The higher the evaluation $Eval(a)$, the partition U/R_a is considered to be similar to the set of decision classes U/R_D. In particular, the partition U/R_a is identical to U/R_D if and only if $Eval(a) = 1$ holds, i.e., the evaluation of a is the maximum value.

On the other hand, the minimum values of evaluation scores by (7) are generally different between condition attributes. Thus, for strictly comparing evaluation scores, we need to normalize the evaluation scores by (7). Here, we introduce the normalized evaluation score of each condition attribute $a \in C$ by

$$NE(a) = \frac{Eval(a) - Min(a)}{1 - Min(a)}, \tag{8}$$

where $Min(a)$ is the theoretical minimum score of $Eval(a)$ defined by the following equation.

$$Min(a) = \frac{1}{2}\left(\frac{|U/R_a| + |U/R_d|}{\min\left(|U/R_a| \cdot |U/R_d|, |U|\right)} \right). \tag{9}$$

Note that the equation (9) is based on the following results [5]:

$$ACer(a) = \frac{|U/R_a|}{\text{Num. of rules by } a}, \; ACov(a) = \frac{|U/R_d|}{\text{Num. of rules by } a},$$

and the following fact that the minimum number of decision rules $(a,x) \to (d,x)$ $(\forall x \in U)$ constructed from $a \in C$ is calculated by $\min\left(|U/R_a| \cdot |U/R_d|, |U|\right)$. We omit the detail of (9) because of space limitation. It is easy to confirm that the range of scores of the normalized evaluation criterion by (8) is $0 \le NE(a) \le 1$.

From the viewpoint of computational complexity, it is easy to confirm that calculation of the normalized evaluation criterion by (8) is polynomial order and therefore the calculation of (8) for all questions in a questionnaire is easier than the calculation of DoC.

3. EXPERIMENT

Twenty healthy male students aged from 20 to 26 participated in this study as subjects. They were well informed about the aim and contents of this study before the experiment, and confirmed their participation by subscribing to the agreement. Subjects were required to answer the "profile of mood state" (POMS) (Japanese version) [8], which is a psychological questionnaire described later, and collect their saliva for 3 minutes. The experiment was conducted in the afternoon from 1 p.m. to 4 p.m. when diurnal change of IgA would be small enough. Collected saliva was kept in a freezer at -20 Celsius immediately after saliva sampling before biochemical assay. The concentration of IgA was determined by the enzyme-linked immunosorbent assay (ELISA). The psychological questionnaire we introduced in this experiment, POMS, is one of the major questionnaire which consists of 65 items asking about subjects' mood with 5 point scale: not at all, a little, moderately, quite a lot, and extremely. These items are designed to classify into the six identified mood factors: Tension-Anxiety (T-A), Depression-Dejection (D), Anger-Hostility (A-H), Fatigue-Inertia (F), Vigor-Activity (V), and Confusion-Bewilderment (C). The score of each mood factors is calculated by adding the corresponding items. Also, there are seven items which are nothing to do with the mood factors (thus these are the dummy item).

As for the rough set analysis, as a simple attempt, IgA was assigned as the only decision attribute, and all the items corresponding to each mood factor were assigned as condition attributes.

4. RESULT

As a result of biochemical analysis, the salivary IgA concentrations of subjects were between 60 and 337$[\mu g/dl]$ (average = 123.5$[\mu g/dl]$, Standard deviation = 63.5). Note that the IgA of a subject was lost because of the failure of biochemical determination procedure. Thus, the data of the rest 19 subjects were introduced by the correlation and rough set analysis described below. Table 2 shows the correlation coefficients between IgA concentration and the six identified mood factors of POMS. As the table shows, there is no statistically significant correlation between the IgA concentration and the mood factors of POMS except for the factor 'C'. Also, the correlation coefficient of C is relatively small (-0.47). Therefore, as the past similar studies have suggested, we can say that there is no relation between factors of POMS and secretion of IgA.

In the next, we categorized IgA data into four non-parametric scales for applying rough set theory, because it is basically non-parametric data analysis method. Also, So far as we know, there is no epidemiological study assessing huge number of subject and showing the distribution (or normal range) of salivary IgA. We thus simply categorized IgA at regular intervals as Table 3 shows.

Table 4 shows the normalized evaluation scores (N.E.) defined by (8) and the Spearman's rank-correlation coefficients of items corresponding to the six identified mood factors and dummy items of POMS. The correlation coefficients are shown only if they are statistically significant ($p<0.05$). There are several items showing statistically significant correlation in factor ``T-A'', 'D', 'F', 'C', and among dummy items. Also all the items in factor T-A, D, F, and C show negative correlation. But mostly the correlation coefficients are still small. The only two items, the item No. 5 in factor C and the No. 57 in factor F, show higher negative correlation ($\rho < -0.7$). Note that such negative correlation is the result of simple one-to-one correlation between each item and IgA. Therefore, it is not necessary to think that the items with higher correlation are more important than the other items in the corresponding mood factor. By the result of Table 2 again, we can say that most of the items and factors of POMS may not relevant to the secretion of IgA.

On the other hand, there are several items with relatively higher evaluation scores (N. E. $\geq$ 0.3) such as the item No. 33 in T-A, No. 47 and No. 48 in D, and No. 11 in A-H.

Table 2. Correlation coefficient between IgA concentration and the six identified mood factors of POMS

	T-A	D	A-H	V	F	C
IgA concentration	-0.22	-0.32	0.00	0.04	-0.41	-0.47*

*p<0.05

Table 3. Categorized IgA at regular interval

	Range of IgA concentration $[\mu g/dl]$	score
Low	< 100	1
Relatively low	100 – 150	2
Relatively high	150 – 200	3
High	> 200	4

Table 4. Evaluation scores of questionnaires and Separman's rank-correlation coefficients between questionnaires and IgA

Factor T-A

Q.	N.E.	Corr.
14	0.22	
18	0.21	
23	0.15	
33	0.35	
36	0.21	-0.50
49	0.23	
53	0.21	
58	0.20	
65	0.15	

Factor D

Q.	N.E.	Corr.
2	0.26	-0.55
7	0.23	-0.47
12	0.20	
16	0.18	-0.53
20	0.20	
24	0.28	
29	0.20	
37	0.23	
42	0.20	
47	0.33	-0.50
48	0.33	-0.67
51	0.23	
55	0.20	
59	0.20	
64	0.26	-0.55

Factjor A-H

Q.	N.E.	Corr.
3	0.15	
8	0.20	
11	0.30	
17	0.21	
21	0.23	
28	0.20	
38	0.20	
41	0.28	
48	0.28	
53	0.08	
56	0.26	
63	0.26	

Factor V

Q.	N.E.	Corr.
4	0.14	
15	0.20	
19	0.23	
26	0.20	
39	0.20	
50	0.26	
54	0.11	
61	0.26	

Factor F

Q.	N.E.	Corr.
9	0.28	
22	0.20	
27	0.23	-0.55
34	0.18	-0.54
44	0.23	
57	0.26	-0.79
62	0.26	-0.64

Factor C

Q.	N.E.	Corr.
5	0.28	-0.70
10	0.16	
25	0.20	
32	0.28	
40	0.28	-0.69
45	0.28	
60	0.23	

Factor Dm

Q.	N.E.	Corr.
1	0.18	
6	0.21	0.46
13	0.20	
30	0.26	
31	0.28	
35	0.20	
43	0.20	0.47

5. DISCUSSION AND CONCLUSION

Our result of correlation in Table 2 supports the results of past studies which indicate that there is no clear evidence showing the close relationship between the daily stresses estimated by some questionnaires and salivary IgA secretion. However, according to a recent review article [2], past studies investigating the relationship between IgA secretion and daily stresses had some methodological defects or discrepancy, such as using non-standardized questionnaires for estimating daily stresses, timing of saliva correction which might be critical if IgA would show circadian secretion rhythm, the number of subjects, etc.

On the other hand, in this study, we calculated normalized evaluation scores (N. E.) of questionnaires defined by (8) based on rough set theory, and found that there were some items with relatively higher evaluation scores. In contrast to the simple one-to-one correlation analysis shown in Table 2, the N. E. represents items relatively more important than the other items in the corresponding mood factor of POMS. In other words, these items marked relatively higher N. E. scores could be useful to presume the IgA level. N. E. evaluates similarity of partitions constructed from condition attributes and the set of decision classes, and does not assume linear relationship between each condition attribute and the decision attribute. Moreover, from the definition (8), N. E. is applicable to evaluation between any set of condition attributes and any set of decision attributes if we used plural decision attributes.

This study is an attempt for introducing rough set into psychoneuroimmunological study. There are hundreds of stuffs to develop this study such as analyzing the other kinds of psychological questionnaires with large number of subjects, assaying the other biomarkers which are thought to be changed according to the psychological states, introducing physiological indices such as heart rate and blood pressure, and taking account of all the possible mediators such as gender, age, race, and/or life styles and habits. The advantage of using rough set analysis is that one could compare among any non-parametric factors. In addition, any factor could be assigned as the condition or decision attributes. Moreover, there is no restriction of the number of decision attributes, and one could choose several factors as the decision attributes. This property would be useful especially to eliminate or detect the possible mediators.

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