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Noninvasive evaluation of mental stress using by a refined rough set technique based on biomedical signals

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ABSTRACT

Objective: Evaluating and treating of stress can substantially benefits to people with health problems. Currently, mental stress evaluated using medical questionnaires. However, the accuracy of this evaluation method is questionable because of variations caused by factors such as cultural differences and individual subjectivity. Measuring of biomedical signals is an effective method for estimating mental stress that enables this problem to be overcome. However, the relationship between the levels of mental stress and biomedical signals remain poorly understood.
Methods and materials: A refined rough set algorithm is proposed to determine the relationship between mental stress and biomedical signals, this algorithm combines rough set theory with a hybrid Taguchi-genetic algorithm, called RS-HTGA. Two parameters were used for evaluating the performance of the proposed RS-HTGA method. A dataset obtained from a practice clinic comprising 362 cases (196 male, 166 female) was adopted to evaluate the performance of the proposed approach.
Results: The empirical results indicate that the proposed method can achieve acceptable accuracy in medical practice. Furthermore, the proposed method was successfully used to identify the relationship between mental stress levels and bio-medical signals. In addition, the comparison between the RS-HTGA and a support vector machine (SVM) method indicated that both methods yield good results. The total averages for sensitivity, specificity, and precision were greater than 96%, the results indicated that both algorithms produced highly accurate results, but a substantial difference in discrimination existed among people with Phase 0 stress. The SVM algorithm shows 89% and the RS-HTGA shows 96%. Therefore, the RS-HTGA is superior to the SVM algorithm. The kappa test results for both algorithms were greater than 0.936, indicating high accuracy and consistency. The area under receiver operating characteristic curve for both the RS-HTGA and a SVM method were greater than 0.77, indicating a good discrimination capability.
Conclusions: In this study, crucial attributes in stress evaluation were successfully recognized using biomedical signals, thereby enabling the conservation of medical resources and elucidating the mapping relationship between levels of mental stress and candidate attributes. In addition, we developed a prototype system for mental stress evaluation that can be used to provide benefits in medical practice.

1. Introduction

An increasing body of evidence supports the hypothesis that stress plays a critical role in chronic disease; specifically, numerous studies have proved that stress produces psychological, physical, and behavioral effects. In addition, previous studies have identified a growing number of chronic ailments associated with stress, such as headache, high blood pressure, and cardiovascular disease, and have indicated that the growth of stress in modern society increases the risk of developing such conditions [1,2]. Therefore, evaluating and treating of stress can lead to improvements in health.

Biomedical signals have been proved to be useful in treating various physical and psychological problems. However, several aspects of using this technique are complex. For example, evaluating and

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treating of mental stress, a limited number of experts are available to correctly classify the levels of stress, and inexperienced clinicians might initially have difficulty in classifying patients [3]. The results of a literature review indicated that few well-designed investigations have been conducted in the field of the stress evaluation. Numerous studies have described the monitoring of heart rate variability (HRV) to evaluate mental stress [4–7]. In addition, recent studies have evaluated variations in mental stress levels by measuring finger temperature [3] and peripheral blood flow, and by using electrogastrograms [8]. Thus, new concepts for stress evaluation have been introduced and considerable advances have been made in this field.

One of the challenges of applying the emerging methods is determining the relationship between biomedical signals and mental stress. Furthermore, a medical database often contains uncertain reasoning, inconsistent information, and lists of attributes that are irrelevant to clinical diagnosis. This causes applying conventional statistical methods and interpreting data to be excessively difficult; therefore, an intelligent decision-making support system based on biomedical signals must be developed to enable clinicians to accurately diagnose health problems related to stress.

This paper introduces a new method for evaluating mental stress. However, discussion on whether the proposed method or other methods yield optimal results is not included because it is irrelevant to the purpose of this study, given that numerous factors, including the dependence on attribute data quality, discretization, and the sampling methods, algorithms, and evaluation methods used, can influence the accuracy of classification. The purpose of this study was to resolve the problems encountered in stress evaluation by using biomedical signals and applying a machine learning method that is similar to the reasoning process of experts and can be represented linguistically.

Rough set theory (RST) can be applied to manage the uncertainty of inference without requiring external information, and to extract knowledge from a medical database. However, the performance of this method might deteriorate when the number of attributes sharply increases or when the dataset grows rapidly. Consequently, the computational efforts associated with conducting searches for attributes must be reduced. The hybrid Taguchi-genetic algorithm (HTGA) provides more favorable performance than does other searching methods [9]; therefore, this study adopted the HTGA to optimize the number of attributes obtained in a reduct computation task for RST. To investigate the relationship between levels of stress and biomedical signals, a refined RST approach combining RST with a HTGA algorithm, called the RS-HTGA is proposed.

The remainder of this paper is organized as follows: Section 2 introduces related studies and describes the research motivation, and the application of RST in medicine. Section 3 describes the methodology. Section 4 presents the experimental results and Section 5 provides includes a detailed discussion on the concerns associated with the relevance of findings to medical practice and the reasons for using the HTGA to reduce attribute. Section 6 presents the conclusions of the study.

2. Related works

2.1. Problems associated with diagnosing stress

In current practice, physicians generally evaluate stress by administering questionnaires. However, various factors, such as individual subjectivity and cultural differences, can strongly influence the accuracy of diagnosis.

To avoid these drawbacks, in this study, biomedical signals were used in a stress evaluation technique in which data were collected from a non-invasive diagnostic device that uses light wave resonance to determine the functional status of the human body. However, because the relationship between stress level and biomedical signals remains unclear, a decision support system must be developed.

2.2. Rough set theory and its application in medical science

Studies on the application of RST in medical research are presented as follows. In 1999, Komorowski and Øhrn [10] introduced a RST and Boolean reasoning approach for predicting of cardiac disease. A decade later, Ningler et al. [11] used an enhanced variable precision RST to conduct electroencephalographic analysis. The advantage of this improved method was that it enabled uncertain objects to change class information during the process of attribute reduction and generation, thereby enabling attribute reduction to be achieved when data are noisy or inconsistent, and providing small rule sets. Liu and Zeng [12] recently proposed a two-layer breast cancer prognosis model in which the RST and support vector machine (SVM) classification methods were integrated. In their study, the rough set served as the first layer, in which singular samples were identified in the data, and the SVM acted as the second layer in which the remaining samples were classified. Wang et al. [13] proposed a hybrid approach that combined RST and particle swarm optimization to reduce the number of attributes, and used it to select features and rules for predicting the degree of malignancy in brain glioma. Tsumoto et al. successfully applied RST in identifying positive and negative rules in clinical databases comprising data related to headaches, cerebrovascular disease, and meningitis. They stated that the rules discovered using RST closely resembled those derived from the reasoning of medical experts [14]. Michalowski et al. [6] developed a mobile clinical support system for pediatric emergencies based on RST and the fuzzy system for evaluating patients with abnormal pain by classifying the most relevant clinical symptoms and signs. Hirano and Tsumoto [4] used approximations to reflect inconsistencies between the knowledge-driven shapes and image-driven shapes in regions of interest. Britka et al. [15] speculated that the most crucial aspect of medical informatics is learning from low-level data obtaining new insight into unknown phenomena, and developing classifier predictors for vague and unclear cases; therefore, they used RST to design a model for analyzing this issue.

2.3. Rough set theory

Pawlak [16] first proposed rough sets theory in the early 1980s. RST has been employed in various domains, including the information, electrical, environmental, engineering, medical, economics, finance, social science, chemical science, and decision analysis domains. In addition, RST can be used in the classification analysis of data tables and removes redundant conditional attributes according to two approximation concepts (lower and upper approximations). RST is based on the original data only and it does not require external information. Several key concepts of RST are described briefly as follows:

Let $I=(U,A)$ be an information system where U is a non-empty set of finite objects, called the universe; A is a nonempty finite set of attributes such that $a: U \rightarrow V_a$ for every $a \in A$; V_a is the value set for attribute a. In a decision system, $A=\{C \cup D\}$ where C is a non-empty set for conditional attributes and D is a non-empty set of decision attributes.

2.3.1. Indiscernibility

All $P \subseteq A$ involve an equivalence relation $IND(P)$:

$$IND(P) = \{(x, y) \in U^2 | \forall a \in P, a(x) = a(y)\} \quad (1)$$