Real-Time Detection of Internet Addiction Using Reinforcement Learning System

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ABSTRACT

[1]Since Internet addiction (IA) was reported in 1996, research on IA assessment has attracted considerable interest. The development of a real-time detector system can help communities, educational institutes, or clinics immediately assess the risk of IA in Internet users. However, current questionnaires were designed to ask Internet users to self-report their Internet experiences for at least 6 months. Physiological measurements were used to assist questionnaires in the short-term assessment of IA, but physiological properties cannot assess IA in real-time due to a lack of algorithms. Therefore, the real-time detection of IA is still a work in progress. In this study, we adopted an extended classifier system with continuous real-coded variables (XCSR), which can solve the non-Markovian problem with continuous real-values to produce optimal policy, and determine high-risk and low-risk IA using Chen Internet addiction scale (CIAS) data or respiratory instantaneous frequency (IF) components of Internet users as input information. The result shows that the classification accuracy of XCSR can reach close to 100%. We also used XCSR to verify the items of CIAS and extract important respiratory indexes to assess IA. We expect that a real-time detector that immediately assesses the risk of IA may be designed in this way.

CCS CONCEPTS

• **Computing methodologies** → **Machine learning** → **Machine learning approaches** → Rule learning • **Applied computing** → **Life and medical sciences** → Health informatics

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KEYWORDS

reinforcement learning system, extended classifier system with continuous real-coded variables, Internet addiction, instantaneous respiratory frequency

1 INTRODUCTION

Internet use has shown explosive growth. Using the Internet makes our life more convenient, but some users exhibit problematic behaviors, e.g. overuse, dependency, and obsession with the Internet. Prof. Young first described problematic Internet use as Internet addiction (IA) in 1996 [1] and found that IA may negatively affect a users' relationships, educational opportunities, and work performances. Because problematic Internet game use is an obvious type of IA, the 5th Edition of Diagnostic and Statistical Manual of Mental Disorders announced the 9 criteria of Internet gaming disorder (IGD) [2]. Moreover, the 11th Revision of International Statistical Classification of Diseases included the gaming disorder in 2018 [3]. Research on IA has become an important topic. To date, the prevalent rate of IA in Asia ranges from 5.6% to 55.9% [4], [5], [6], [7]. In Europe, it ranges from 7.94% to 37.5% [8], [9], in Australia it ranges from 4.0% to 46.7 % [10], [11] in America it is 8.1 % [12].

For the past two decades, IA has mainly been assessed using IA-related questionnaires. However, the assessment of IA faces challenges related to real-time discrimination. For example, the Taiwan government and researchers wildly applied the Chen Internet addiction scale (CIAS) for adolescents and found that those surveys were usually adopted to assess the experiences of Internet users for at least 6 months [4]. Internet users have to spend a lot of time on self-reporting. Many psychological properties have been organized into the questionnaires that may increase the time needed to fill it out and decrease the willingness of the user to do so. Although physiological measurements are adopted to assist questionnaires in the short-time assessment of IA, physiological properties from physiological signals cannot dynamically and immediately assess IA due to the lack of algorithms. Researchers have not yet proposed suitable methods for the real-time detection of the IA problem.

The extended classifier system with continuous real-coded variables (XCSR) [13] is a reinforcement learning (RL) system, which is an agent to interact with dynamical change environments and extract a rule for each interaction. Each rule is represented "IF condition THEN action" and one presented symbol # denotes a bit with ignoring, called "don't care". In this study, we apply CIAS data as input information to XCSR for IA-risk determination. Then, we use rule of # in XCSR to verify the free items of CIAS. To compare different input information, we also apply the ensemble empirical mode decomposition (EEMD) method to decompose the physiological signals [14], i.e. combining with XCSR to extract physiological properties of IA risk. Two contributions of this paper are: to first propose a RL system for IA determination, and then to verify the items of the CIAS questionnaire. We expect that the two contributions can be adopted while designing a system for the real-time detection of IA, and provide insight into the psychophysiological properties of persons with IA and assist with clinical diagnosis and subsequent treatment.

The organization of this study is as follows. Section 2 presents the empirical study of IA-related questionnaires and the physiological measurement of individuals with IA. Section 3 describes the structure of XCSR. The experimental processes for collecting questionnaire and measuring respiratory signals, and the parameter setup of XCSR are shown in Section 4. Section 5 exhibits the results of classifier accuracy for XCSR via CIAS and respiratory signal, and we then discuss our findings in this study. The last section summarizes the study and proffers future work.

2 RELATED WORK

People with IA exhibit overuse and addiction to the Internet. They are always thinking of their previous Internet use or anticipating their next Internet use. Their tolerance symptom makes them need to spend more time on the Internet to achieve gratification or excitement. They try repeatedly to reduce or stop their Internet use but fail in their efforts. When they attempt to reduce their Internet use, they feel unpleasant or negative physical effects. To use the Internet, they spend less time on other activities or with family and friends. They even give up educational and work opportunities. IA negatively affects Internet users' relationships, educational opportunities, and work performances. In spite of these consequences, people with IA still continue using the Internet. The above-mentioned psychological properties would be organized into IA-related questionnaires to assess IA symptoms [1], [2], [4], [15].

Although IA-related questionnaires have been discussed for two decades, the assessment of IA faces challenges in real-time detection. First, the number of psychological properties organized into an IA-related questionnaire is still under debate. The design of IA-related questionnaires can be affected by different countries, areas, ages, and translation. This causes unstable questionnaire design. For instance, CIAS revision was widely used to assess IA in the Chinese society. Initially, CIAS

Table 1: The outline of S_C, S_W, S_T, PI_H, and P_{TM} properties in CIAS and explanation of each property.

Property	Item and Explanation
S_C	11. I cannot control my impulse to use Internet. 14. When I wake up every morning, my first thought is to use the Internet. 19. After stopping Internet usage, I crave it again. 20. Without the Internet, my life would be joyless. 22. I try to spend less time on the Internet, but I fail.
S_W	2. I feel displeasure when I stop using the Internet for period of time. 4. I feel restless and irritable when the Internet is unavailable. 5. I feel energetic upon using the Internet regardless of a fatigued experience. 10. I feel distressed when I stop using the Internet for a period of time. 16. I feel like I am missing something when I stop using the Internet for a period of time.
S_T	3. I perceive my Internet use as getting longer and longer. 6. I spend more time on the Internet than I originally intended. 9. I have spent more time on the Internet since last semester. 24. I need to increase the amount of time I use the Internet to achieve the same satisfaction as before.
P_{IH}	7. Even if the Internet has negative consequences on my interpersonal relationships, my usage remains unreduced. 12. I find that I reduce the time spent with friends due to the Internet. 13. I feel aches and soreness in my back or other discomfort due to Internet use. 15. Using Internet has negative effects on my education or work. 17. I reduced interaction with my family due to Internet use. 18. I reduce my recreational activities to use the Internet. 21. Using the Internet has negative effects on my health.
P_{TM}	1. I have been told more than once that I spend too much time on Internet. 8. My sleep time is less than 4 hours from using the Internet. 23. I am used to reducing my sleep time to use the Internet. 25. I do not eat on time due to using the Internet. 26. I use the Internet all night, which causes daytime tiredness.

was composed of five psychological properties, namely, compulsive symptoms (S_C), withdrawal symptoms (S_W), tolerance symptoms (S_T), time management problems (P_{TM}), and interpersonal and health-related problems (P_{IH}). Chen et al. proposed that the S_C should be combined with S_W into S_{CW}, and the items of CIAS were modified from 28 to 24. But, Chen et al. separated S_{CW} into SC and S_W again, and the items of CIAS were revised to 26 for Taiwan's young adults [4]. The numbers of included items were 5, 5, 4, 7, and 5 for S_C, S_W, S_T, P_{IH}, and P_{TM}, respectively. Table 1 outlines the psychological properties in 26 items of CIAS and the individual explanation of each property (modified from [16]). Mak et al. also indicated that S_C should be combined with S_W, and the items of CIAS were changed to 19 for Hong Kong adolescents [17]. In addition, IA-related questionnaires were usually adopted to assess the experience of Internet use at least 6 months after activities (named narrative surveys). IA-related questionnaires were also used to assess the current experiences of Internet use after activities (named activity surveys). But few IA-related questionnaires assess the current experiences of Internet use during activities (named as experience sampling method, ESM). The adoption of current IA-related questionnaires to assess the immediate experience of Internet use is a limitation. Therefore, the psychological properties in IA-related questionnaires is an important issue.

In recent years, researchers have adopted physiological measurements to assist IA-related questionnaires in the short-term assessment of IA. Researchers measured Internet users' heart rate, blood pressure, respiratory signals, skin conductance, or other physiological responses during more than 3-min Internet-related cues stimuli to observe the physiological properties of people with IA. e.g., the breathing rate and blood flow pulse of 27 individuals with high-risk IA (HIA) were higher than those of 25 individuals with lower-risk IA (LIA) [5]. The respiratory sinus arrhythmia value of 19 individuals with HIA [18] and skin conductance of 27 individuals with HIA [5] were lower than those of individuals with LIA. Compared with the control group, cardiorespiratory coupling of 22 individuals with excessive online gaming [19] and log high frequency of 38 individuals with Internet gaming addiction [7] during gaming were reduced. 16 individuals with IA after gaming [8] and 27 individuals with IA during higher punishment [9] had increased skin conductance levels. Of the physiological responses, control of respiration can regulate other psychological and physiological responses. In clinical treatment, 39 patients did breathing exercises to reduce their IA symptoms [20] and 30 persons with IGD attended to control their breathing to regulate their emotions [21]. 45 persons who overused their smartphones did Yoga breathing exercises to relax muscle aches [22]. Therefore, respiratory responses are an important index to IA diagnosis and treatment. Although physiological responses are important indexes to assist with the assessment of IA, extracting physiological properties cannot be used for the real-time assessment of IA due to algorithms.

Factor analysis (FA) is commonly used to extract psychological properties from IA-related questionnaires of narrative and activity survey types. The result presents a single dimension to observe the psychological properties in IA-related questionnaires. FA, however, is not often used to analyze non-Markovian problems and continuous real-value data. This method is unable to extract psychological properties from IA-related questionnaires of ESM type. Descriptive statistics are used to extract the physiological properties of individuals with IA from physiological signals. Descriptive statistics, however, are not often used to analyze instantaneous physiological signals and non-Markovian problems. Descriptive statistics are unable to extract physiological properties for the immediate assessment of IA. Dr. Lin et al. used a mobile application (App) to collect smartphone users' behavior, including daily use count and duration and the media of the duration to detect smartphone addiction [23]. Although, App would not interfere with smartphone users to detect smartphone addiction, App spends much time collecting users' behaviors.

3 REINFORCEMENT LEARNING SYSTEM

Regarding the aforementioned limitations, we select XCSR to solve the problem of the real-time detection of IA. The extended classifier system (XCS) is an evolutionary computation method, and the concept of using XCS is matching the past memory and current input to produce optimal policy [24]. Moreover, XCS can be modified into XCSR for analyzing continuous real-value data. We decide to use XCSR as a determination method for IA.

3.1 eXtended Classifier System (XCS)

XCS has been extended by many researchers as a rule-based machine learning method that combines RL and Evolutionary Computation (EC). The biggest feature of XCS is that the learned rules are human-readable. A rule is stated as "IF condition THEN action", which means that if the condition is met, then the action is executed. Therefore, there are many encoding types of condition and action. The original coding of XCS selects the ternary alphabet {0, 1, #} in the condition part of the rule and the binary {0, 1} as the action. The symbol # is the biggest spot light of XCS. # can be interpreted as "don't care", meaning that the input of corresponding bit can be accepted regardless of whether it is a 0 or 1. XCS solves the optimization problem by cooperation and competition between a set of rules. The set of rules is called population set [P]; the number of rules is limited. To assess the quality of the rules and find whether a rule is suitable for survival in the [P], XCS uses 3 evaluation parameters: (*i*) Prediction (p): Predict how many rewards we will get from the environment after executing the action. (ii) Prediction Error (ε): The difference in value between the predicted reward and the actual reward. (iii) Fitness (F): Judging by the quality of the rules, if the Prediction Error is smaller, the greater the Fitness of the rule. In XCS, rules contain evaluation parameters called classifiers. XCS will modify the [P] to maximize the reward by constantly interacting with the environment. The role of the Genetic Algorithm (GA) in XCS is to help XCS produce better classifiers.

3.2 eXtended Classifier System with Continuous Real-Coded Variables (XCSR)

XCSR is a variant of XCS used to process continuous real-value data. The biggest difference in XCSR is that it changes the condition of the classifier from the original ternary alphabet expression to an interval predicate. The interval predicate contains two important values: the intermediate value, and the range value. The expression of the interval predicate is $int_i = (c_i, s_i)$, where c_i is intermediate value and s_i is the range value; the alphabet s stands for the "spread." The schematic illustration of XCSR is shown in Fig. 1. An iterative procedure of XCSR consists of 4 steps, as follows.

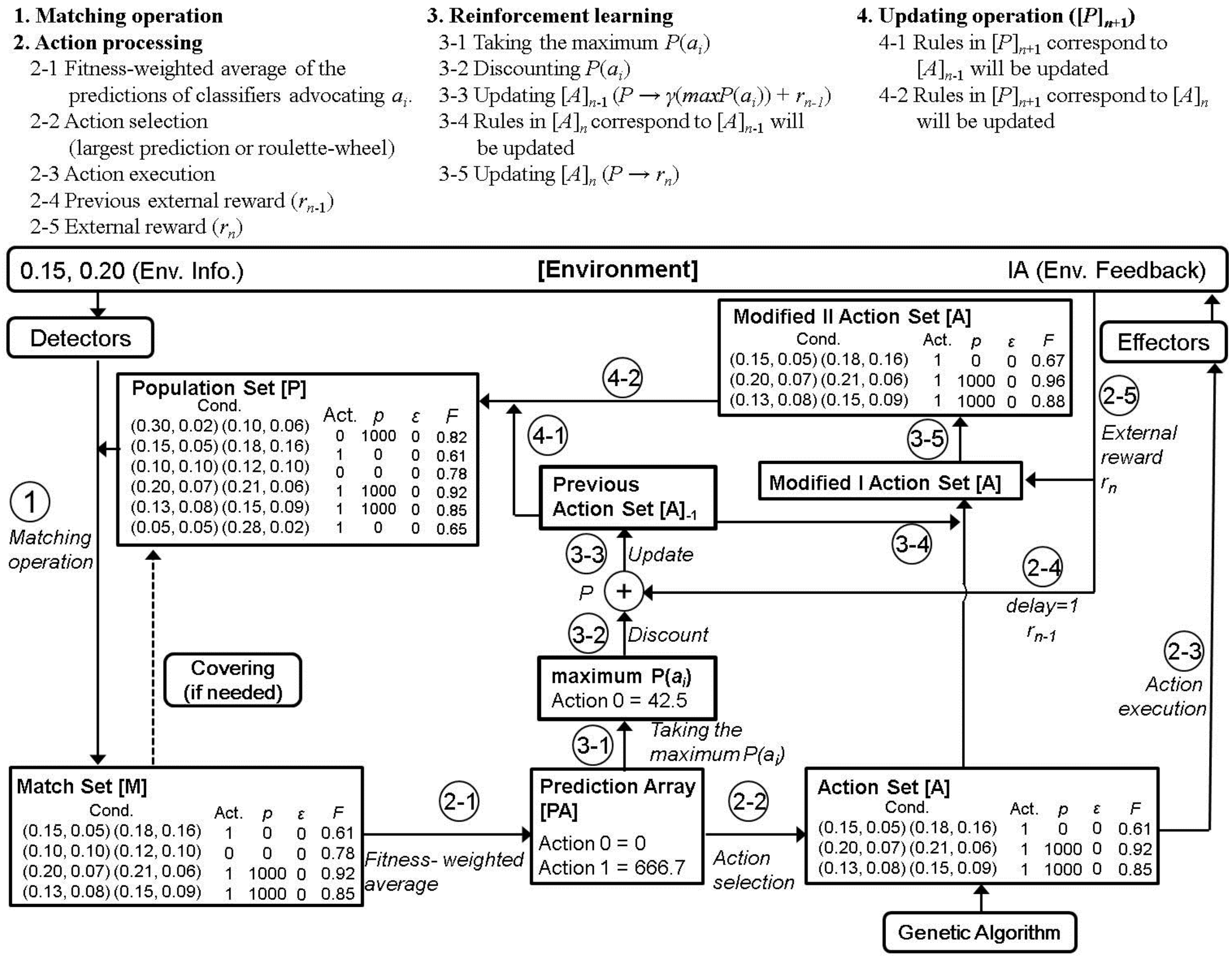

Figure 1: The schematic of XCSR consists of 4 steps, namely matching operation, action processing, reinforcement learning, and updating operation.

1) Matching operation: XCSR encodes the environmental information into the expression recognized by XCSR through the detectors. Next, XCSR compares the condition of each classifier from [P] with the environmental information. If the environmental information x_i falls within the range of (c_i - $s_i \le x_i \le c_i + s_i$), the x_i is considered to match the classifier's condition. This matched classifier will be put into match set [M]. If [P] is searched without any matching and [M] is still an empty set, XCSR activates the covering mechanism. Covering is a function which generates a classifier whose conditions meet x_i with a random action and put the new classifier into [M]. The condition of a new classifier is expressed as $int_i = (c_i, s_i)$, where c_i is equal to x_i and s_i is a random number greater than 0 and less than s_r; s_r is defined by the user. The parameters of the initial classifiers are given randomly. After the covering is completed, XCSR searches [P] again and must match a classifier.

2) Action processing: XCSR uses the fitness-weighted average of predictions of the classifiers with the same action in [M] as the predicted reward of the action. Based on the weighted value, XCSR selects the action to be executed by using the maximum predicted value or roulette-wheel method. The action of the classifier in [M] which is the same as the action selected by XCSR will be put into action set [A]. The selected action will be executed through the effector, and the environment will give rewards based on the actions executed.

3) RL: XCSR uses Q-learning to update the Prediction, Prediction Error, and Fitness according to the reward given by the environment in [A].

4) Updating operation: Classifiers in [P] that correspond to [A] have to be updated.

XCSR will repeat the 4 steps given above till the termination condition is met. In addition to these 4 steps, GA will activate when XCSR meets the threshold for GA. GA mainly contains two major mechanisms: crossover and mutation. GA uses uniform crossover to exchange the corresponding interval predicate in the condition with 2 classifiers with probability x. The mutation randomly adjusts the range value of the interval predicate at a certain probability. XCSR adds and subtracts a random value from 0 to *m* for c_i and s_i, where *m* is defined by user. In addition to GA, XCSR includes a subsumption mechanism, which implies that more general and correct classifiers will include other classifiers. General in XCSR means that the interval predicate contains a larger range. Subsumption in XCSR converges to the optimal solution faster.

4 EXPERIMENT

In this section, we are going to describe the experimental procedure for collecting CIAS and acquiring respiratory signals. In addition, the parameter setup for XCSR is shown.

4.1 The Experimental Procedure

36 men and 14 women in the age range of 20—40 years were directly recruited from the main campus of National Chiao Tung University (NCTU), Hsinchu, Taiwan. Before this recruitment, ethical approval was obtained from the NCTU Research Ethics Committee for Human Subject Protection (Approval No: NCTU-REC-102-009-e). Each participant was asked to fill out CIAS (26 items, 4-point Likert scale from 1 (extreme disagreement) to 4 (extreme agreement)) [4]. The maximum and minimum values of CIAS are 104 and 26. In literature, the cut-off score of 63/64 is suggested as an indication for separating participants into LIA (scores < 64) and HIA (scores ≥ 64) [6]. We also asked each participant to fill out an IGD questionnaire (IGDQ, 9 items, 2-point Likert scale form 0 (disagreement) to 1 (agreement)) [2]. The cut-off score is 4/5 which divides participants into with IGD and without IGD [25].

In the experimental procedure, participants watched a gray picture for relaxing psychological and physiological responses. Next, the participants completed three trials, where each trial consisted of rest status (watching the gray picture for 2 min), stimuli status (watching a game film for 2 min), recovery status (watching the gray picture for 2 min), and self-report status (filling out self-assessment manikin (SAM) [26] questionnaire)). The design of the four statuses was to relax psychophysiology, arouse emotions, relax psychophysiology again, and assess emotional valence and arousal, respectively. Regarding the game film, we selected MapleStory (Nexon Corp., Seoul, Korea), League of Legends (Riot Games, Inc., Los Angeles, USA), and Resident Evil (Capcom Co., Ltd., Osaka, Japan) because these films corresponded to the most popular games in the NCTU campus. Moreover, we treated these three films as neutrally, positively, and negatively emotional stimuli, respectively [27]. To get the instantaneous frequency (IF) of breathing, the respiratory inductance plethysmography (RIP, RIPmate Inductance Belt, Abdomen Kit, Adult, Alice 5, Ambu Inc., Denmark) is adopted to measure the simultaneous abdominal

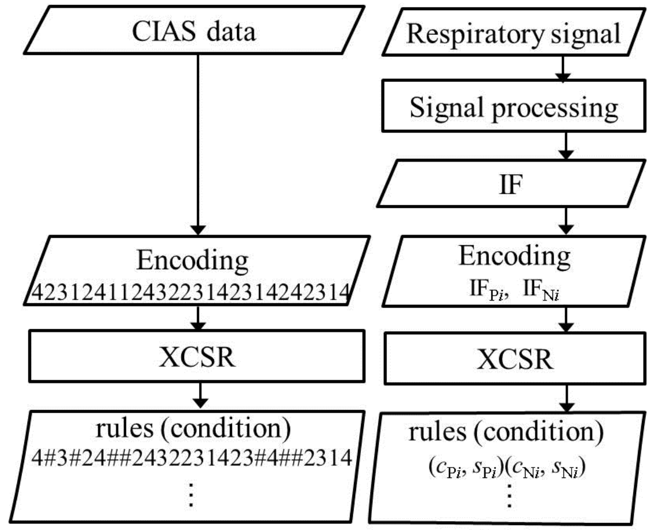

Figure 2: The analysis procedure of CIAS data and respiratory signals frequency during positive game stimuli (IF_P) and negative game stimuli (IF_N) as input. (*i* = 1–8 in this study)

Algorithm 1 Analysis procedure of the EMD

$x_1(t) \leftarrow x(t)$
$s(t) \leftarrow x(t)$
for $i = 1$ to N **do**
\\ sifting process
  while ($SD(s(t)) \geq 0.02$) do
    $p_u \leftarrow$ TheLocalMaxima($s(t)$)
    $p_l \leftarrow$ TheLocalMinima($s(t)$)
    $u(t) \leftarrow$InterpolatingTheLocalMaxima(p_u)
    $l(t) \leftarrow$InterpolatingTheLocalMinima(p_l)
    $m(t) \leftarrow (u(t) + l(t))/2$
    $s(t) \leftarrow s(t) - m(t)$
  end
  $IMF_i(t) \leftarrow s(t)$
  $x_{i+1}(t) \leftarrow x_i(t) - IMF_i(t)$
  $s(t) \leftarrow x(t) - s(t)$
end

SD($s(t)$): standard deviation of $s(t)$

wall movement of participants during the three trials. The sampling rate of the signal was 1,000 samples/sec.

4.2 The Analysis Procedure

The analysis procedure for XCSR is shown in Fig. 2. The 26 items of CIAS and the average of respiratory IF during positive game stimuli (called IF_P) and negative game stimuli (called IF_N) were treated as the input information for XCSR. The signal processing consists of two parts: preprocessing and transformation. The preprocessing part consisted of calculating the integral of abdominal wall movement signal, linear fit, down sampling to 50 samples/sec, and the EEMD method [14]. The EEMD as an adaptive filter was used to decompose signals into intrinsic mode functions (IMFs), ordering them from high to low frequency oscillatory components. The analysis procedure of EEMD considers that signals add white noise and executes empirical mode decomposition (EMD). Algorithm 1 exhibits the analysis procedure of the EMD (modified from [28]). In this paper, 8 IMFs are decomposed from respiratory wall movement signals by EEMD. Our previous study showed that each IMF represents different physiological components, i.e. diaphragm, respiratory muscle clusters, and respiratory wall movement [29]. On the basis of breathing frequency bandwidth, this study recognized IMF1–IMF2, IMF3–IMF4, IMF5–IMF6, and IMF7–IMF8 as the different components of diaphragm, respiratory muscle cluster, respiratory wall movement, and body movement, respectively. During the transformation part of signal processing, the normalized direct quadrature [30] was adopted to calculate the corresponding IF. The average of IF was input to XCSR. Fig. 3 illustrates a respiratory wall movement signal of an individual with LIA and the corresponding 8 IFs of 8 IMFs.

Based on empirical studies [13], [24], [31], the parameters of XCSR are configured as follows. The population size *(N)* is 350. The probability of # (P#) at an allele position is 0.33 for the initial population. The initial rule p, initial rule ε, and initial rule *F* are 10, 0, and 10, respectively. The accuracy function (ε_0) is 10. The learning rate (β) is 0.2. The other parameters for F calculation of a classifier condition are α= 0.1, ε_0= 10, and ν= 5. The discount factor (γ) is 0.71. The probability of crossover operation (χ) is 0.8, and the probability of mutation operation (μ) is 0.04. The covering mechanism occurs when the total prediction of [M] is less than the product of ϕ times the mean of [P], where ϕ = 0.1 in this study. The threshold parameter of GA operation is 25. Both the deletion and subsumption thresholds of GA operation are 20. The reward (*p*) setup for HIA with IGD and LIA without IGD are 1,000 and 0, respectively. The functions for data acquisition, signal processing, and XCSR operation were implemented in a LabVIEW environment (v.2016, NI Corp., Austin, USA).

Additionally, the operating characteristic curve (ROC) method was used to evaluate the predictive ability of IF with XCSR. The area under the curve (AUC) and 95% confidence interval (lower and upper bound) were calculated. AUC values higher than 0.5 indicate diagnostic ability.

5 RESULT AND DISCUSSION

Based on the conventional questionnaire, there are only 19 (24 ± 5 years old) and 21 (23 ± 2 years old) participants belonging to HIA with IGD and LIA without IGD, respectively. As one participant was missing respiratory signals, 18 and 21 participants for HIA with IGD and LIA without IGD, respectively, were included for RL. All accuracy is calculated by the moving average per 50 exploitations for XCSR. Figs. 4 and 5 illustrate the classification accuracy (%) of the average of 30 replications for

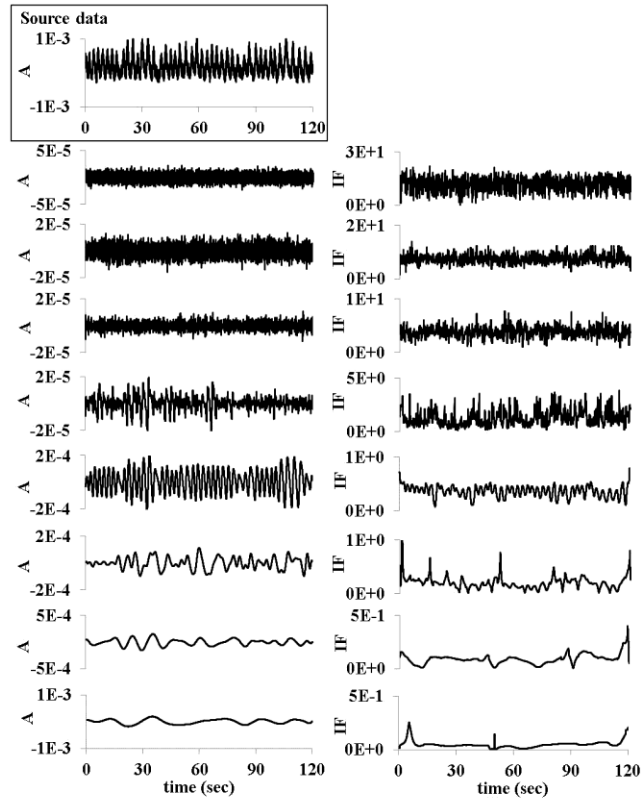

Figure 3: One of respiratory wall movement signals (source data) during negative game stimuli was decomposed into 8 IMFs and the corresponding IFs. (A: amplitude, IF: instantaneous frequency)

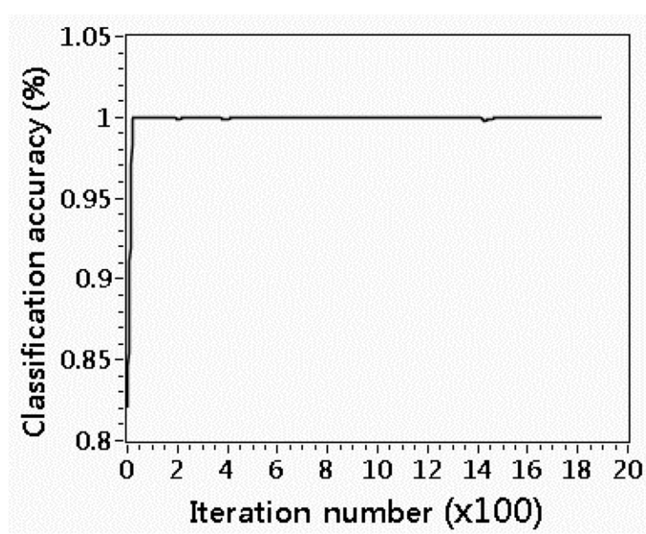

Figure 4: The classification accuracy of 30 replications of XCSR for CIAS data.

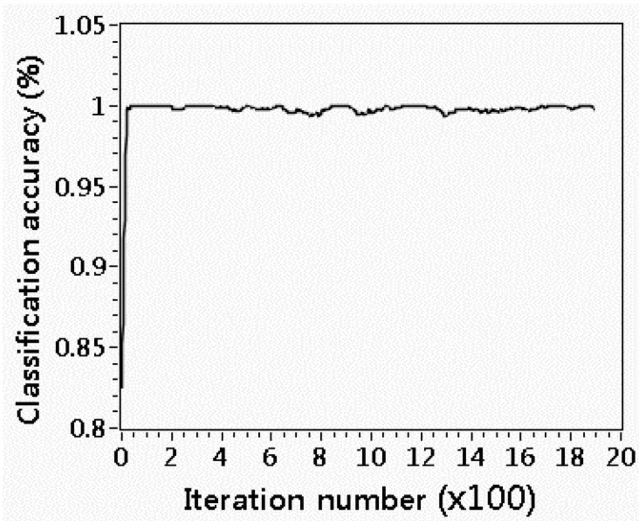

Figure 5: The classification accuracy of 30 replications of XCSR for respiratory instantaneous frequency signals.

XCSR with iteration number of 1,950 by using CIAS data and IF values, respectively. Because the accuracy values are close to 100%, we concluded that XCSR can be effectively used to determine the risk level of IA. The respiratory IF components can also be an important index.

Regarding the verification of CIAS items and the extraction of the properties of respiratory IF, we observed rules with HIA with IGD, p = 1000 in [P], and we then calculated the probability of appearing # on the selected numerosity rules. Table 2 lists the probability values for CIAS and IF data. Because there are 5 psychological properties of CIAS, the probability values are listed for individual items of the corresponding properties. We found that the important item of CIAS is different for participants. We setup a threshold of 50% to reduce the item selection. The 11th, 14th, 19th, and 22nd items in S_C; the 2nd, 4th, 10th, and 16th items in S_W; only the 6th in S_T; the 12th, 13th, 15th, 17th, 18th, and 21st items in P_{IH}; and the 1st, 8th, 23rd, and 25th items in P_{TM} were retained in CIAS. We suggested that XCSR can be used to verify the items in CIAS. This finding may provide researchers an insight into the risk symptoms of IA in Taiwan's adults so they can re-design the corresponding assessment questionnaire of ESM type.

Table 2 also lists the probability values for 8 respiratory IFs data during positive stimuli and during negative stimuli. Probability values ranging from 30.8% to 66.7% for IMFs are represented for different physiological components [29]. Our previous study [6] showed that the amplitudes of abdominal muscle contraction and respiratory wall movement of individuals with HIA and LIA exhibited different tendencies during positive and negative emotional stimuli. Our finding in this study indicated that XCSR can further extract the leading components for IA determination. If the threshold is set to 50% to enhance the leading components, the IF_{P1}, IF_{P2}, IF_{P4}, IF_{P6}, IF_{P8},

Table 2: The # probability for CIAS and IF data. (P*i*: IF component during positive emotional stimuli; N*i*: IF component during negative emotional stimuli; *i*: 1~8)

CIAS data (# probability, %)								
S_C	**11th**	**14th**	**19th**	**20th**	**22nd**			
	41.7	25.0	33.3	58.3	33.3			
S_W	**2nd**	**4th**	**5th**	**10th**	**16th**			
	41.7	25.0	50.0	16.7	25.0			
S_T	**3rd**	**6th**	**9th**	**24th**				
	50.0	41.7	66.7	58.3				
P_{IH}	**7th**	**12th**	**13th**	**15th**	**17th**	**18th**	**21st**	
	58.3	33.3	8.3	25.0	41.7	33.3	16.7	
P_{TM}	**1st**	**8th**	**23rd**	**25th**	**26th**			
	41.7	33.3	33.3	41.7	50.0			
IF data (# probability, %)								
Positive stimuli	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**
	46.2	43.6	51.3	43.6	53.8	41.0	66.7	38.5
Negative stimuli	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
	30.8	51.3	51.3	41.0	69.2	46.2	46.2	51.3

Table 3: The AUC of ROC with 95% confidence interval for IF_P and IF_N predicting HIA with IGD and LIA without IGD. (P*i*: IF component during positive emotional stimuli; N*i*: IF component during negative emotional stimuli; *i*: 1~8)

			95% Confidence Interval	
IF	**AUC**	**p-value**	**lower bound**	**upper bound**
P1	0.52	0.82	0.33	0.71
P2	0.52	0.80	0.33	0.71
P3	0.58	0.41	0.39	0.76
P4	0.53	0.74	0.35	0.72
P5	0.56	0.55	0.37	0.74
P6	0.49	0.96	0.31	0.68
P7	0.63	0.17	0.45	0.81
P8	0.50	0.98	0.31	0.68
N1	0.54	0.63	0.36	0.73
N2	0.70	0.03	0.51	0.89
N3	0.67	0.07	0.48	0.86
N4	0.64	0.14	0.45	0.82
N5	0.52	0.87	0.32	0.71
N6	0.67	0.07	0.50	0.84
N7	0.58	0.41	0.39	0.76
N8	0.52	0.82	0.33	0.71

IF_{N1}, IF_{N4}, IF_{N6}, and IF_{N7} were retained. Compared to the studies on [5], [6], our finding provides more able indexes of respiratory responses to assess IA risk, such as diaphragm, respiratory muscles, and body movement responses. Additionally, we found that XCSR extracted different respiratory properties for data during positive and negative stimuli. In contrast to the situation during negative stimuli, the diaphragm with high frequency during positive stimuli is used to assess IA. It is possible that different emotional stimuli cause different respiratory muscles responses [32].

Table 3 shows the AUC of ROC with 95% confidence interval (lower and upper bound) for the IF_P and the IF_N predicting HIA with IGD and LIA without IGD. The result indicated that IF_{N2} (AUC = 0.70, p-value = 0.03), IF_{N3} (AUC = 0.67, p-value = 0.07), and IF_{N6} (AUC = 0.67, p-value = 0.07) were potential indexes in predicting the risk of IA. The results in Table 2 are different from the results in Table 3. A possible reason for this is that the ROC method adopts a single dimension to calculate the IF_P and IF_N predicting IA, and the XCSR method adopts a multidimensional approach to predicting IA. Nevertheless, XCSR shows potential in extracting important indexes for the assessment of IA. In the future, we would like to collect more samples to support this finding.

Our research has three limitations. First, due to the small sample size problem on CIAS data, the earning data size is too small to cause significant difference to the # probability. Second, due to the novelty of our research, our finding is limited to XCSR, lacking other RL for verification. Finally, this study investigates the CIAS based on the parameters of [13], [23], [31] due to RL inheritance. Nevertheless, we proposed an RL for HIA with IGD and LIA without IGD discrimination through CIAS data and respiratory IF data. We also compared the items of CIAS and extracted the effective respiratory components for ESM assessment. This way might provide a way for IA-related questionnaires to be designed for different countries, areas, and ages for further ESM implementation. We expect that this model can design a system that will not interfere with Internet users during the real-time detection of the risk level of IA in users.

6 CONCLUSION AND FUTURE WORK

To conclude, this study first proposes XCSR to the application of IA examination. The dataset for 39 participants with CIAS, 8 IF signals under positive stimuli, and 8 IF signals under negative stimuli are used as environmental information for XCSR learning. The results show that the classification accuracy of XCSR can reach close to 100% for all data. We infer that XCSR is an effective learning classifier system to discriminate HIA and LIA. Moreover, we found that XCSR may reduce the items of CIAS from 26 to 19, i.e. 11^{th}, 14^{th}, 19^{th}, and 22^{nd} items in S_C; 2^{nd}, 4^{th}, 10^{th}, and 16^{th} items in S_W; 6^{th} in ST; the 12^{th}, 13^{th}, 15^{th}, 17^{th}, 18^{th}, and 21^{st} items in PIH; and 1^{st}, 8^{th}, 23^{rd}, and 25^{th} items in PTM of CIAS as the leading psychophysiological properties. In addition, XCSR can also reduce the respiratory instantaneous frequency components from 8 to 5 (positive stimuli) and 4 (negative stimuli), i.e. the IF_{P1}, IF_{P2}, IF_{P4}, IF_{P6}, IF_{P8}, IF_{N1}, IF_{N4}, IF_{N6}, and IF_{N7} of breathing rate as leading physiological properties. We expect this model to be used to design a system for the real-time detection of the risk of IA in Internet users. In the near future, we would like to verify our findings in reinforcement learning with a field test and find the optimal parameters for XCSR.

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