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IQ Classification via Brainwave Features: Review on Artificial Intelligence Techniques

Aisyah Hartini Jahidin, Mohd Nasir Taib, Nooritawati Md Tahir, Megat Syahirul Amin Megat Ali
Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia

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ABSTRACT

Intelligence study is one of keystone to distinguish individual differences in cognitive psychology. Conventional psychometric tests are limited in terms of assessment time, and existence of biasness issues. Apart from that, there is still lack in knowledge to classify IQ based on EEG signals and intelligent signal processing (ISP) technique. ISP purpose is to extract as much information as possible from signal and noise data using learning and/or other smart techniques. Therefore, as a first attempt in classifying IQ feature via scientific approach, it is important to identify a relevant technique with prominent paradigm that is suitable for this area of application. Thus, this article reviews several ISP approaches to provide consolidated source of information. This in particular focuses on prominent paradigm that suitable for pattern classification in biomedical area. The review leads to selection of ANN since it has been widely implemented for pattern classification in biomedical engineering.

Corresponding Author:

Aisyah Hartini Jahidin,
Faculty of Electrical Engineering,
Universiti Teknologi MARA,
40450 Shah Alam, Selangor, Malaysia.
Email: aisyah23@gmail.com

1. INTRODUCTION

Cognitive ability is a sub-division of human potential which refers to individual's characteristic approach in information processing. This has been well-established within the domain of human intelligence and is strictly related to intelligence quotient (IQ). To date, IQ is assessable using conventional methods such as Stanford-Binet Intelligence Scales [1], Raven's Progressive Matrices [2], and Wechsler Intelligence Scales [3], which can then be quantified for evaluation of mental performance. A drawback to these type of assessment are that it is relatively insensitive to individual understanding in answering the psychometric tests. Moreover, there would be biasness issue that is unique to each of the assessment batteries [2, 4]. Certainly, EEG has become increasingly important as it can record vast amounts of complex neuronal activity from the human brain. Thus, the qualitative information can be overcome with quantitative measurement provided by the EEG.

In general, EEG can be categorized into primary and secondary signals. A primary EEG can be observed and interpreted directly during the EEG recording. These signals have been utilized extensively to assist clinicians in diagnosing acute paediatric encephalopathy [5], anaesthesia [6], stroke [7], schizophrenia [8], and dementias or Alzheimer [9]. Under severe cases, it is also used to ascertain brain death [10]. Meanwhile, the secondary EEG is used for more sophisticated applications. This however, would require complex data processing approaches for signal manipulation. The secondary EEG have been implemented in person recognition [11], and brain–computer interface [12], as well as investigation on neurophysiological correlates with psychophysiology, which normally includes emotion recognition studies [13] and its effects from external stimulus [14]. Other application of EEG can also be related to cognitive abilities such as intelligence [15] and learning style [16].

The features extracted from raw EEG signals without losing its original content are crucial in order to distinguish and classify brain activity effectively. This would enable correlation of parameters with the neuropsychological functioning of the brain. With the aid of various signal processing approaches, characterisations of brainwave features in the past have taken numerous approaches under a broad perspective of EEG studies [17-19]. Such valuable information obtained through innovative signal processing is commonly incorporated with the use of intelligent classifiers and hence, result in the conception of intelligent signal processing (ISP) technique. The approach refers to the implementation of model-free techniques for feature extraction and modelling purposes [20]. These would further contribute to the enhancement of knowledge and lead to a wider range multidisciplinary applications. Certainly, this presents an excellent opportunity to advance the research in relating EEG with IQ via ISP.

Currently, there is a variety of artificial intelligence (AI) techiques [21-24] that could be incorporated for IQ classification via the brainwave features. In order to justify the selection of a particular method, the paper attempts to provide a general overview and applications of established techniques, which are expert system, genetic algorithm, fuzzy logic and artificial neural network (ANN) [21-24]. The discussion then focuses on selection of ANN as suitable ISP method for classification of IQ index based on EEG.

2. ESTABLISHED INTELLIGENT SIGNAL PROCESSING APPROACHES

Throughout the years, pattern recognition and classification has been made possible via ISP that specifically focuses on analyzing and modelling of complex data. The aim of ISP is to extract as much information as possible from signal and noise data using dedicated learning techniques [25]. ISP differs fundamentally from the classical approach of statistical signal processing in that the input-output behaviour of a complex system is modelled using intelligent or model-free techniques, rather than relying on the limitations of mathematical models [20]. To achieve such goals, numerous methods can be utilised; each having its own unique advantages and drawbacks. Therefore, it is important to identify a particular ISP technique that could meet the specifications required for modelling the relationship between IQ and brainwave features.

There are wide varieties of ISP techniques currently available. However, this paper will only focus on techniques most commonly found in the literature. These comprise of expert systems, genetic algorithms, fuzzy logic and ANN. It is noted that the methods originate from human-related phenomena and an offspring of broader discipline known as AI. In general, the techniques exhibit similar characteristics of simple computational stages, and often complemented by repetitive learning cycle [26].

It has been implemented in diverse areas, such as science [27], engineering [27, 28], agriculture [27, 29-33], medical [27, 34-41], biomedical [34, 42, 43], computer science [27], and financial [44, 45]. The application paradigms include control, design, diagnosis, instruction, interpretation, monitoring, planning, pattern classification, prescription, prediction, selection, scheduling, maintenance and targeting, optimisation, identification, clustering and feature extractuin [27-32, 34, 35, 37-39, 44-78]. Table 1 summarises each ISP approach with the respective application paradigms.

Table 1. Summary of ISP Technique and Application Paradigms

Techniques	Application Paradigms	Areas
Expert System	control [27, 57], design [27], prescription [27], diagnosis [27, 28, 31, 34-37, 56, 57] , sorting [29], identification [30], instruction, interpretation, monitoring [38, 57], selection [44], managing [45], planning [59], classification [32], prediction [63]	chemistry [27], geology [27], space technology [27], electric railway [28], egg grading [29], plant protection in pepper [30], fish disease diagnosis [31], pollen grains identificaition [32], computer networks 43], stock exchange [44], finance management [45], health [56], industrial [57], drug metabolism [63].
Genertic Algorithm	optimization [68-71, 73, 74], identification [78], scheduling [65, 66], feature extraction [67], control [68],	epilepsy stage identification, industrial, power system, environment, electromagnetics related to antenna, medical physics, control theory, and economics [67, 70, 74, 79-81].
Fuzzy Logic	Control [75, 76, 82-84], decision making [60], monitoring[39], diagnosis [40], identification [85], pattern recognition/classification [40, 42, 76]	robotic [84], industrial (automotive) [82], power [83], geoscience [86], instrumentation [87], stock trading [60], typhoid fever [40], multifunctional prosthesis control [42].
ANN	Control [24, 64], function approximation, prediction [33, 77], pattern classification [88-92], forecasting [93], clustering/categorisation, diagnosis [94],	fuel consumption in wheat production [33], sleep scoring [43], risk in dengue patients [77], post-dialysis blood urea concentration [41], robotics and machine embodiments, adaptive control of complex systems, power [95], manufacturing, transportation [88], electric nose sensors [96], environmental system [97], energy systems [33], epilepsy [92] .

Expert system is knowledge-based algorithm that emulates the behaviour of human experts in terms of thought and reasoning process [98]. The expert systems can designed as a problem-solving ability model, which involves knowledge, reasoning, conclusion and explanations similar to human expert in order to analyse and solve complex problems [27]. The first expert system was developed in the mid-1960s [21], but its application proliferated in the 1980s [27, 99]. The technique is suitable for closed-system applications for which inputs are literal and precise, leading to logical outputs [98]. Throughout the years, its implementation is mostly intended for diagnosis purposes [27]. Expert systems have a profound application in health diagnostic systems [34, 36, 38, 39, 59], which interpret medical test results [27].

Conversely, genetic algorithm is a solution searching technique, which is rooted in the ideas of evolution process and natural population genetics [74]. The technique that was conceptualized by John Holland in the 1960s, has driven the interest in heuristic search algorithms with foundations in natural and physical processes [79]. Its most prominent implementation is in optimization [68-71, 73, 74]. Consequently, genetic algorithm is most successful in solving problems that are related to characterization in physical sciences [74]. Another ISP technique, the fuzzy logic was founded in 1965 by Lofti Zadeh [23]. The concept was adopted from human thinking and much resembles the natural language compared to the traditional logical systems [75]. Within the next two decades, fuzzy logic has been widely implemented to solve problems from decision-making theory. The technique is most successfully applied in control problems [64, 75, 76, 82-84]. The system however, is not capable of learning [100]. Hence, its implementation in the area of pattern recognition is still limited. To minimize such drawback, fuzzy logic will need to be integrated with other ISP techniques [42, 87].

Meanwhile, ANN is a non-linear artificial intelligence approach that is inspired by the working of biological neurons in the brain [101]. The technique that was introduced in the 1940s has recently seen a sharp increase in its implementation [24]. ANN has been an alternative to the traditional statistical modelling techniques in various scientific disciplines [102]. Its main advantage lies in its ability to learn and generalize solutions for complex problems [101]. Hence, the method is particularly useful for solving a probem for which large amount of data is involved, but with unknown inter-relationship [102]. It can approximate the non-linear relationship between the input variables and the output of a sophisticated system [103]. Implementation of the ANN can be mostly found in biomedical applications [46, 47, 52]. Moreover, it was also discovered that ANN has been very successful when integrated with innovative signal processing approach for pattern recognition purposes [88-91, 104].

3. COMPARATIVE ANALYSIS

Table 2 summarizes on the selection criterias for the comparative analysis. The selection criteria include capabilities to generalize solution for complex problems, to self-learn, analyze and model non-linear relationships, as well as its primary purpose of implementation.

Table 2. Selection Criterias

	Criterias	ES	GA	FL	ANN
1	Generalize Solution for Complex Problems	Yes	Yes	No	Yes
2	Self-learning Capability	No	Yes	No	Yes
3	Analyze and Model Non-linear Relationships	No	No	No	Yes
4	Purpose of Implementation	Diagnosis	Optimization	Decision-making	Pattern recognition

Up to this point, it has been identified that ANN is the most suitable approach to be implemented for IQ modelling via the EEG. This is attributed by its previous successes as a robust modelling technique in biomedical applications, particularly for pattern recognition and classification. Thus, the following section will further elaborate on the important aspects of ANN which include its most popular architecture.

3.1. Artificial Neural Network

ANN was pioneered by McCulloch and Pitts in the 1940s. Later, the perceptron convergence theorem has been introduced by Rosenblatt in the 1960s [101]. Despite this, the theory was still having its limitations, which resulted in slowdown of the research area. However, the enthusiasm resurged in 1982 with the introduction of back-propagation learning algorithm by Werbos for the multilayer perceptron network. In 1986 [24], it was further popularized by Rumelhart. Ever since, the use of ANN has seen a steady growth with applications spaning across a wide range of problem domains as previously mention in Table 1.

The multilayer perceptron is currently the most established supervised neural network model for practical applications in solving diverse and complex problems [91]. As an intelligent technique, the multilayer perceptron has been widely used for optimisation, modelling, prediction and function approximation purposes [105]. However, it has also been successfully applied to a variety of pattern recognition and classification problems [54, 55]. Such applications include disease recognition [77], physiological analysis and modeling [46], cancer detection and classification [47], modelling of heart disease recognition [106], diagnosis of coronary artery disease [49], and other related studies [52, 89].

3.2. Integration of Artificial Neural Network and EEG for IQ Classification

Implementation of ANN in biomedical application has been observed in signal compression, enhancement and interpretation [89]. The proposed research on IQ classification via brainwave features fall within the domain of signal interpretation, whereby the pattern of EEG sub-band features will be recognized through a learning process and later classified into discrete IQ levels [107]. An uncompromising advantage of ANN also lies in the ability to cross-correlate data correctly from unknown relationships.

ANN has certainly established itself as the most successfully modelling technique for biomedical applications [52, 108], particularly in the area of pattern recognition [54]. Over the years, several types of ANN have been developed, each with unique properties that make them more suitable for certain task over the others. The network architecture varies in terms of structure, activation function and learning algorithm. In general, the ANN can be implemented in supervised and unsupervised learning modes [109]. Under the former setting, the network will have to recognize the pattern only from the input variables. Conversely, the later will allow the network to learn by recognizing the relationship between the input variables and the output. Hence in our proposed work, the network will be implemented in supervised learning settings whereby the EEG features will be assigned as the inputs and the distinct IQ levels as the actual output. This would allow the network to be trained by confirming its performance to the provided output.

4. CONCLUSION

Among various ISP approaches, the ANN is perceived as a significant technique for pattern recognition and classification through its modelling capabilities. Its implementation has extended to a wide range of biomedical applications. Thus, ANN is considered as the most suitable method to model the IQ from brainwave features.

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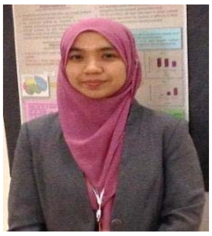
BIOGRAPHIES OF AUTHORS



Aisyah Hartini Jahidin obtained the B.Eng (Telecommunication) and M.Eng.Sc (Electrical) from Universiti Malaya, Malaysia. She is currently a postgraduate researcher at the Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia. Her main research interests include human intelligence, cognitive ability, EEG and non-linear modelling of brain behavior via intelligent signal processing technique.

Mohd Nasir Taib obtained the B.Eng (Electrical) from the University of Tasmania, Australia, M.Sc. (Control Systems) from University of Sheffield, and Ph.D. (Control & Instrumentation) from University of Manchester Institute of Science and Technology, United Kingdom. He is currently a Professor and the Dean of the Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia. He is leading an active research group and supervising a pool of researchers in advanced signal processing with applications in control systems and process, biomedical engineering, and nonlinear systems.

Nooritawati Md Tahir received the B.Eng (Electronics) from the Universiti Teknologi MARA, Malaysia, M.Sc. (Microelectronics & Telecommunications) from University of Liverpool, United Kingdom, and Ph.D. in Electrical Engineering (Pattern Recognition & Artificial Intelligence) from Universiti Kebangsaan Malaysia, Malaysia. She is currently an Associate Professor at the Faculty of Electrical Engineering and the Director of Research Innovation Business Unit, Universiti Teknologi MARA, Malaysia. Her research interests include image processing, pattern recognition, computer vision and artificial intelligence.

Megat Syahirul Amin Megat Ali received the B.Eng (Biomedical) from Universiti Malaya, Malaysia, and M.Sc. (Biomedical Engineering) from University of Surrey, United Kingdom. He is currently a senior lecturer at the Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia. His research interests include EEG and intelligent modelling of brain behavior with application to experiential learning theory.