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EEG-based biometric authentication modelling using incremental fuzzy-rough nearest neighbour technique

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Abstract: This paper proposes an Incremental Fuzzy-Rough Nearest Neighbour (IncFRNN) technique for biometric authentication modelling using feature extracted visual evoked. Only small training set is needed for model initialisation. The embedded heuristic update method adjusts the knowledge granules incrementally to maintain all representative electroencephalogram (EEG) signal patterns and eliminate those rarely used. It reshapes the personalized knowledge granules through insertion and deletion of a test object, based on similarity measures. A predefined window size can be used to reduce the overall processing time. This proposed algorithm was verified with test data from 37 healthy subjects. Signal pre-processing steps on segmentation, filtering and artefact rejection were carried out to improve the data quality before model building. The experimental paradigm was designed in three different conditions to evaluate the authentication performance of the IncFRNN technique against the benchmarked incremental K-Nearest Neighbour (KNN) technique. The performance was measured in terms of accuracy, area under the Receiver Operating Characteristic (ROC) curve (AUC) and Cohen's Kappa coefficient. The proposed IncFRNN technique is proven to be statistically better than the KNN technique in the controlled window size environment. Future work will focus on the use of dynamic data features to improve the robustness of the proposed model.

1 Introduction

Biometric authentication involves either confirmation or denial of the identity that a user is claiming. An identity authentication system has to deal with two kinds of events: either the person claiming a given identity is the one s/he claims to be (client) or s/he is not (impostor). Such a system is important in ensuring security for access to highly restricted areas. Biometric authentication systems using various modalities such as fingerprint, facial, voice, iris and hand geometry are easily violated and prone to forgery by third parties. In consequence, an alternative biometric feature, i.e. an electroencephalogram (EEG) is proposed as a more secure biometric modality. Biometric authentication using brainwaves aims to differentiate the client from impostors based on the distinctive features hidden in EEG signals. Since every living person has recordable EEG signals, these signals are universal. Furthermore, brain damage is a very rare occurrence and the brain never rests.

However, EEG signals are non-stationary and hard to reproduce, because they may be influenced by environmental and physiological noise. The research on analysing visual evoked potentials (VEPs) for biometric authentication using soft computing modelling is very limited and rarely pays attention to uncertainty methods, even though uncertainty modelling has proved to be efficient in many other domains. As a combination of both notions from fuzzy and rough sets theory, the fuzzy-rough nearest neighbour (FRNN) model is outstanding to model uncertainty under an imperfect data condition. However, many real-world applications also involve conditions that change over time. The current implementation of the FRNN technique is not designed for incremental learning problems, because there is no update function to incrementally reshape and reform the existing knowledge granules. Incremental changes are merely treated as noise, unless the training pool is updated with new training objects. The current incremental approach can be applied to the FRNN algorithm to transform it into an incremental model as has been done to the KNN [1] and support vector machine (SVM) [2] models. However, the incremental strategy of KNN is a first-in–first-out (FIFO) strategy [1] while incremental SVM includes the data incrementally and discards the previous data, apart from their SVs [2]. This is not a good implementation for biometric authentication modelling, because missed predictions will not be always retained as useful knowledge, due to the object deletion process. Furthermore, adding all new objects to the knowledge base will increase the size of the training pool unnecessarily. Thus, the granularity distribution function in FRNN needs to be incremental and adaptable to accept and facilitate dynamic changes. The proposed incremental FRNN (IncFRNN) embedded a heuristic update method to maintain all representative EEG signal patterns and eliminate those rarely used.

The rest of this paper is organised as follows: Section 2 is a literature review on existing biometric authentication methods and incremental learning. Sections 3 and 4 present the FRNN algorithm and the IncFRNN algorithm, respectively, and Section 5 describes EEG data acquisition. Section 6 outlines the experimentation carried out in this paper, and Section 7 presents and discusses the results, while Section 8 draws conclusion and suggests the direction of future work.

2 Literature review

A biometric is any measurable feature(s), in terms of a physiological or behavioural trait or their combinations, which can be used to authenticate the claimed identity of an individual. It relies on ‘something that you are’ to differentiate between an authorised person and a fraudulent impostor. Physiological biometrics include fingerprints, facial features, hand geometry, iris and retinal characteristics, while behavioural biometrics include voice, keystroke dynamics and gait. The fingerprint authentication system is one of the most popular and oldest biometric authentication systems, but it is not unique, due to forgery issues. In addition, clients with severe finger injuries cannot use it. The facial recognition model is not reliable because the human face structure evolves and changes as the person grows old, and the recognition system is affected by lighting, facial expression, resolution and the hairstyle of an individual. The voice authentication is easy to record and is highly sensitive to environmental noise. The popularity of hand geometry recognition has decreased because it is not unique. The iris is a unique authentication modality, but hard to scan from a distance. Furthermore, the problem of scanning the iris of an individual with eye problems such as cataracts or blindness is still a major challenge to this system. Thus, all the existing biometric authentication methods have shortcomings for high security or restricted areas.

Biometric authentication using brainwaves is used to overcome these shortcomings. It aims to differentiate client from impostors based on the distinctive features hidden in the EEG signals, which have proven to be unique, confidential, difficult to mimic and almost impossible to steal [3–5]. VEP is the representation of brain activities, typically recorded from the occipital scalp when the brain responds to visual stimuli. The use of VEP, reported in [6–9], has proven that EEG signals are suitable for constructing accurate biometric authentication applications. A research study by Zuquete *et al.* [7] showed that EEG signals differed from person to person, even when they were performing the same task or responding to the same visual stimuli. EEG signals can easily be affected, but they cannot be easily reproduced under conditions such as stress, fatigue, anxiety, drowsiness or medication [10]. For example, forcing a person to do something or pointing a gun to their head will create different EEG signals from those of a normal person in a relaxed state. From the security perspective, the EEG-based authentication system will not be immune to phishing attacks and EEG signals will not be 100% identical [11]. Moreover, EEG signals are usually non-linear, non-stationary and hard to reproduce. Thus, the classification of EEG signals is not a trivial task.

An incremental learning model provides a system with the ability to learn from new information when it is available. Incremental learning is particularly relevant because many real-time applications do not have a complete set of data, and learning needs to be an ongoing process [12]. Incremental learning is the online learning process (from the data stream), object by object, based on batch learning. According to Geng and Smith-Miles [13], incremental learning has several benefits:

1. Incremental learning does not require a sufficient training set before the learning process.
2. Incremental learning can learn continuously for improvement when the system is running.
3. Incremental learning is adaptable to changes of the target concept.
4. Incremental learning requires less computation and storage resources than traditional machine learning.
5. Incremental learning naturally matches dynamic applications which depend on time series.

Rough set theory (RST) was first proposed by Pawlak (1982) as an effective tool to deal with uncertainty. It has been successfully applied to many different applications. However, the existing RST literature mainly deals with data from static environments. Recently, RST with incremental updates was introduced to capture the changes in a dynamic environment [14]. RST describes an information system as consisting of three elements: the object (instance); the attribute (feature); moreover, the domain of the attribute's value. The incremental updating approaches suggested from the perspective of rough sets originated from the concepts related to the variation of an object, the variation of an attribute and the variation of an attribute's value. In a pre-processed EEG dataset, the concept of objects indicates the trials from the recordings, while the attributes and attribute's values are represented by the extracted EEG signal features and the respective feature values. Therefore, the information system can be updated from time to time, where there exist a certain range of quantifiable variation among objects. This is driven by the differences in a collection of EEG trials from different recording sessions. In real-world applications, EEG signals might be recorded periodically, in various environments across diverse conditions. Instead of retraining the whole dataset from scratch, incremental RST is suggested to incorporate the new knowledge into the information system when new data arrive. Similarly, by deleting irrelevant objects from the information system computational resources will be conserved.

A commonly used instance-based learner, the KNN is, by its nature, an incremental learning model, due to its lazy training and eager testing modelling strategies. The incremental concept in the KNN algorithm is similar to the variation of the object in incremental RST. The KNN algorithm has been proven useful for EEG signal analysis and many other biometric authentication and identification applications [15]. The training data is first trained in batch learning mode, using the KNN classifier. It stores each new testing object and eliminates the oldest object from the training pool. In other words, the KNN classifier usually applies the FIFO approach to update the training pool incrementally. The new model with the added test object will be used for the next testing phase [12]. However, the FIFO approach is not suitable for biometric authentication modelling, due to the imbalanced data in each class. Classes with more training objects will have a higher tendency to influence the overall prediction. Thus, instead of using the FIFO approach, it is recommended to identify and store only the significant objects while eliminating the rarely used objects [16] for biometric authentication modelling.

3 FRNN algorithm

FRNN was first introduced by Jensen and Cornelis [17]. The FRNN classifier is a hybrid model combining the strength of two natural computing designs, i.e. fuzzy sets and rough sets, and an NN classification approach. FRNN is an extension to the KNN algorithm which employs FRST [18]. Instead of using Euclidean distance, the FRNN calculates the NNs by using similarity. The FRNN classifier can be found in an FR version of the Waikato Environment for Knowledge Analysis (WEKA) data mining tool.

In the FRNN algorithm, the NNs are used to construct fuzzy lower and upper approximations to quantify the membership value of a test object to determine its decision class, and test objects are classified based on their membership of these approximations. The fuzzy lower and upper approximations are constructed to avoid the use of fuzzy logical connectives altogether. Fuzzy logic connectives play an important role in the development of FRST. A triangular norm (t-norm), T, is any increasing, commutative and associative $[0, 1]^2 \rightarrow [0, 1]$ mapping satisfying $T(1, x) = x$, for all x in [0, 1]. On the other hand, an implicator is any $[0, 1]^2 \rightarrow [0, 1]$ mapping 1 satisfying $1(0, 0) = 1$, $1(1, x) = x$, for all x in [0, 1]. In [17], the Kleene–Dienes implicator was used for x, y in [0, 1]. The FRNN algorithm is shown in Fig. 1 [17].

The algorithm is dependent on the choice of a fuzzy tolerance relation, R. In [17], R is constructed as follows.

Given the set of conditional attributes $\mathbb{A}$, R is defined by

$$R(x, y) = \min_{a \in \mathbb{A}} R_a(x, y) \tag{1}$$

in which $R_a(x, y)$ is the degree to which objects x and y are similar in attribute a. There are many other possible options: the FRNN algorithm in [17] used the option as follows:

$$R_a(x, y) = 1 - \frac{|a(x) - a(y)|}{|a_{\max} - a_{\min}|} \tag{2}$$

where σ_a^2 is the variance of attribute a, and $a_{\max}$ and $a_{\min}$ are the maximal and minimal occurring values of that attribute.

Theorem 1: Given a set $\mathbb{U}$ by FRNN, an object y with the greatest similarity will be classified into a class. For example, y will belong to class A, where $\exists x^* \in A,\ \text{s.t.}\ \mu_{R_P}(x^*, y) = \max_{x \in \mathbb{U}} \{\mu_{R_P}(x, y)\}$.

The algorithm in Fig. 1 examines each of the decision classes iteratively in the training data. The membership of the testing data is calculated under the consideration of the lower and upper approximation for each class.

Input: X, the training data; $\mathcal{C}$, the set of decision classes; y, the object to be classified
Output: Classification for y
begin
    $N \leftarrow getNearestNeighbours(y, k)$
    $\tau \leftarrow 0, Class \leftarrow \emptyset$
    for each $C \in \mathcal{C}$ **do**
        if $\big((R \downarrow C)(y) + (R \uparrow C)(y)\big)/2 \geq \tau$ **then**
        $Class \leftarrow C$
        $\tau \leftarrow \big((R \downarrow C)(y) + (R \uparrow C)(y)\big)/2$
        end
    end
    Output Class
End

Fig. 1 *FRNN algorithm [17]*

4 IncFRNN algorithm

As pointed out earlier, classification of EEG signals is challenging, as they are non-stationary and vary over time. EEG signals have very low signal-to-noise ratio, contain outliers and have high dimensionality. Furthermore, the EEG signals may vary over sessions, even for the same subject working on the same mental task. Thus, an incremental classifier is needed to incrementally quantify the signal patterns.

Incremental learning, also known as online learning or adaptive learning, is a machine learning paradigm where the learning process takes place from time to time, whenever new incoming objects emerge, and the model adapts what has been learned according to the new incoming objects. The main advantage of incremental learning is that it does not need a sufficient training set before the learning process, as the training objects appear over time. This is because the learner is able to self-adapt to the changing environment without retraining the whole data. Moreover, classifiers with incremental learning can be used to process large amounts of data, as the training data does not have to fit into the memory. The proposed IncFRNN algorithm flowchart is shown in Fig. 2.

The IncFRNN algorithm is an enhanced version of the FRNN algorithm, which employs incremental learning. All the incremental classifiers only can work in the knowledge flow interface in WEKA. The IncFRNN classifier implements the interface UpdateableClassifier located in package weka.classifiers. The knowledge updating process takes place in the training pool when the object evolves from time to time while the attributes remain unchanged.

The proposed IncFRNN algorithm enhances the original FRNN algorithm [17] by employing a heuristic update method to incrementally reshape and reform the personalised knowledge granules. A new object is being updated selectively into the training pool whenever the learning model encounters new variant of the test objects. By adding in a new object with same data features into the training pool, the knowledge granules will evolve, while maintaining the features that define the biometric identity of a person during the authentication process.

The proposed heuristic update method imposes an incremental strategy of object variation, object insertion and object deletion. Learning model retraining is not required when the training pool changes by inserting an object. Instead, the incremental approach allows the model update to fine tune the learning model. However, continuous insertion of objects may lead to a large training pool. Thus, the selective update of training objects is a preferred strategy. The proposed IncFRNN model controls the size of the training pool by using a window size threshold. Deletion of an object is performed if and only if the number of objects in the training pool is greater than the window size threshold. In summary, the updating strategy in the IncFRNN algorithm will maintain all distinct objects while eliminating the trivial objects.

4.1 Window size threshold

Window size threshold is defined to restrict the number of objects in the training pool. The deletion of objects from the training pool takes place when the window size threshold is defined. The window size threshold determines the maximum number of training objects allowed in the training pool. The value of the window size threshold is initialised as 0. The window size with a value of 0 in the IncFRNN algorithm indicates no limit to the number of objects in the training pool. The size of the training pool is increased when a new object is inserted. It does not involve any deletion of the object from the training pool. However, users have to input a value in order to restrict the number of objects in the training pool.

4.2 Insertion of object

Let a new object x_{10} be inserted into the universe, U, at time $t + 1$ and $U' = U \cup \{x_{10}\}$. In the IncFRNN algorithm, the insertion of an object into the training pool takes place when the test object is incorrectly classified. The main idea for the insertion of an object is to update the knowledge granules with a new object when the existing knowledge granules are unable to predict a new test object. This update will benefit the authentication process whenever the model encounters another similar test object in the future. EEG signals are unique and hard to reproduce, even though the subject performs the same task. Individual characteristics can change over time. Hence, updating the knowledge granules incrementally is important to include the new representative characteristics of an individual. The insertion of objects helps to include the new EEG signals' characteristics in the knowledge granules. Thus, the updating method is crucial to achieve better performance of EEG-based biometric authentication modelling.

4.3 Deletion of object

When the object x_4 is deleted from the universe, U, then $U' = U - \{x_4\}$. In the proposed IncFRNN algorithm, the deletion of an object from the training pool takes place when the threshold of window size is defined. The window size threshold determines the maximum number of training objects allowed in the training pool. The deletion of the object is based on the value of similarity. The NNs concept is the key definition to construct fuzzy lower and upper approximations in the original FRNN model. The highest similarity value is used as the decision quantifier for class assignment, rather than the average membership values of lower approximation and upper approximation. Thus, the classification performance is improved by enhancing the value of similarity in the IncFRNN technique.

A frequency counter has been introduced in the heuristic update method to track the usage frequency for the k NNs. When the number of training objects exceeds the number of window size, the training object with the lowest similarity count within the same class will be deleted. In addition, the IncFRNN algorithm also follows the FIFO strategy in the case when the values of frequency counters for the training objects are the same. Hence, object deletion based on frequency count will store the most representative objects and eliminate the rarely used objects. The object deletion eliminates the rarely used EEG signal patterns which are no longer meaningful to represent the current individual characteristics. The deletion of an object must take place if and

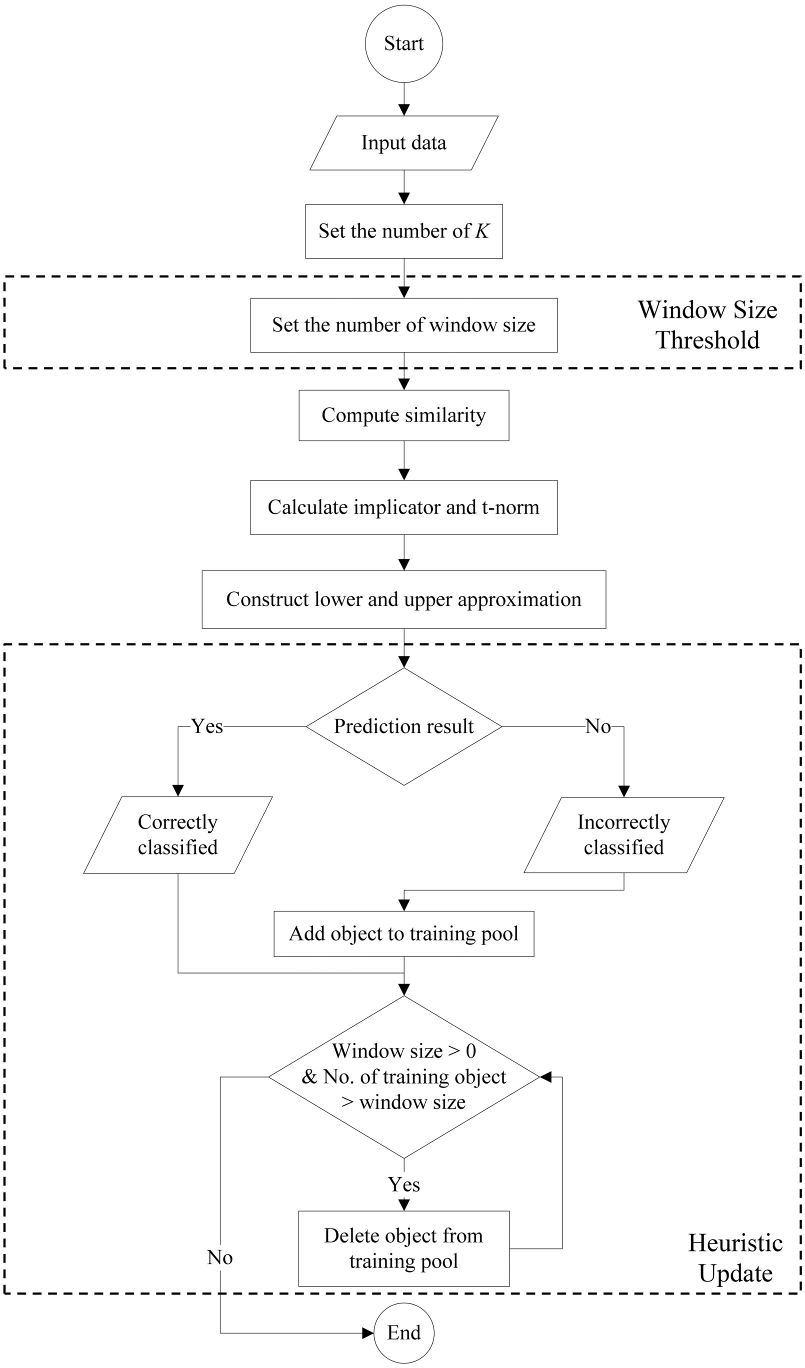

Fig. 2 *IncFRNN flowchart*

only if the window size is <0 and the number of objects in the training pool is greater than the window size.

5 EEG data acquisition

A group of 37 healthy subjects (18 males and 19 females) were recruited to participate voluntarily in the case study. The age of the subjects ranged from 22 to 29 years old. A total of 31 subjects are right-handed while six subjects are left-handed. All the subjects had normal vision or corrected normal vision. Ethical approval had been obtained from the Medical Research and Ethics Committee from Ministry of Health Malaysia. Every subject was explained the experimental procedures and given a written consent form prior to participation in this paper.

The subject was seated on a back-rested chair. The computer display was located 1 m away from the subject's eye level. The pictures were displayed one after another at the centre of the screen with a fixation point. All the stimuli were presented on a white background at the centre of a computer monitor 19.5 cm high and 34.5 cm wide, while the size of stimuli was 700×525 pixels.

Data acquisition was performed in two different environmental conditions: (i) a quiet environment; (ii) the same environment as in (i), but with the addition of an audio clip of recorded office noise effects played through the audio speaker. The subjects were asked to recognise whether the picture displayed on the computer screen was the picture selected by each subject as his or her password. Psychophysics Toolbox Version 3 [19] was used to display the visual presentation. The experiment was completed with 120 trials (60 trials with the selected password picture and 60 trials with a random picture) for each session. The 120 trials were then displayed randomly to the subjects. This paradigm was designed to simulate the dynamically changing ambient noise, causing different EEG signal patterns in different individuals, across the stipulated time frame in the experimental setup. PsychPortAudio command was used to generate a 'pop' sound, and it was synchronised to the visual stimuli presented on the computer screen. The Arduino sound trigger [20] was used to monitor the analogue input and convert the sound wave to Transistor-Transistor Logic (TTL) pulse with the respond rate within 1 ms after receiving the sound pulse.

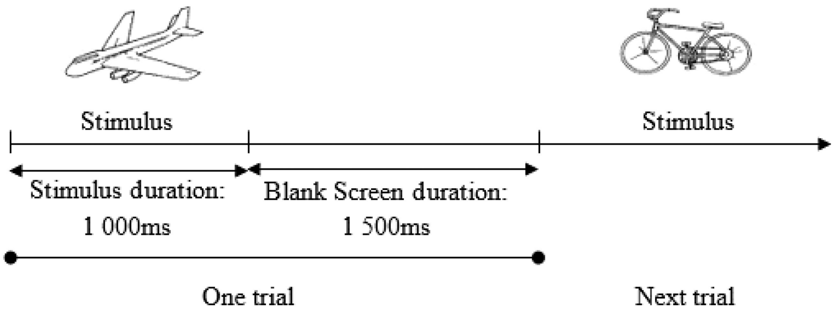

Fig. 3 *Visual stimulus presentation*

Table 1 Experimental setup for three different use case situations

Use case	Description	Aim
perfect situation	data acquired in the quiet environment only were used in both training and testing sets	baseline testing
regular situation	data acquired in both quiet environment and noisy environment were used in both training and testing sets	capability testing
challenging situation	data acquired in both quiet environment and noisy environment were used for testing set; however, only data acquired in quiet environment were used in training set	competence testing

Eight parietal-occipital (PO) and occipital (O) electrodes located at the visual cortex area (i.e. PO7, PO3, POZ, PO4, PO8, O1, OZ and O2) were recorded in the experiment. All the scalp electrodes were referred to A2 and grounded on the left hand in the experiment.

The inter-stimulus interval for each trial was set to 1.5 s. The picture remained on the computer screen for 1 s followed by 1.5 s of white-blank screen, as illustrated in Fig. 3. A 5 min short break was interspersed in between the recording sessions to provide rest time to the subject. This was designed to assure good attention from the subject during the experiments.

The raw data were pre-processed by filtering, segmentation and artefact rejection. The purpose of filtering is to improve the signal quality by minimising the background noise or interference. However, filtering can lead to some information loss [21]. Bandpass filtering with Finite-duration Impulse Response (FIR) type was used and the high-pass and low-pass filters were 1 and 30 Hz, respectively. Segmentation must be performed prior to further analysis including feature extraction, feature selection and classification. The raw EEG signals were segmented based on the stimuli. Artefact rejection is also important to avoid misleading information in signal interpretation. The EEG signals are normally measured from peak to peak and range from 0.5 to 100 µV [22]. Thus, trials with excessive body movements or other types of artefacts with amplitude >100 µV were discarded.

6 Experimentation

6.1 Data preparation

Instead of treating the biometric authentication as a 37-class problem (based on the total number of subjects), the classifier was trained based on a binary class problem, i.e. the client and the impostor. The processed dataset was divided into training and testing data using a ten-fold cross-validation method to ensure unbiased performance measurement. The incremental classifier does not assume the availability of a sufficient training set in the learning process; instead, the training examples will appear over time [13]. Thus, instead of using 90% training data and 10% testing data, the designed ten-fold cross-validation splits the data into 10% training data versus 90% testing data. To evaluate the performance of the proposed model in handling uncertainty and non-stationary signals, the dataset was split into three different situations in the case study as shown in Table 1.

The experimental setup for perfect situation simulated a non-disturbance condition. The recorded EEG signal patterns were more consistent, since most of the subjects were able to concentrate in performing the required VEP tasks in the experiment. The experimental setups for regular and challenging situations were recorded in the simulated environments to mimic the real-world situation in two different conditions, i.e. (i) where ambient noise existed in both training and testing phases and (ii) where ambient noise existed only in the testing phase.

6.2 Feature extraction and feature selection

A new EEG dataset is extracted from the raw dataset using the designated feature extraction methods. The main goal of feature extraction is to extract the feature vectors which are considered as a different observation for the purpose of classification. Feature extraction is one of the ways of reducing dimensionality. It is expected to extract relevant information from the input data instead of using full-sized input data. Single-channel and multiple-channel-features extraction methods were selected based on the literature review. Multiple-channel features involve two different channels to represent joint characteristics between the channels. According to Liew *et al.* [23], six feature extraction methods yielded good results for biometric authentication. Wavelet packet decomposition (WPD) and mean of amplitude are the examples of single-channel methods. Multiple-channel feature extraction methods including mutual information, cross-correlation, coherence and the Hjorth parameter approach were used in this research. Research work in [24] has established that Daubechies with order 4 wavelets and sixth level of WPD is the appropriate parameter in order to analyse EEG signals with 256 Hz sampling rate. Since the frequency of useful EEG signals is lower than 50 Hz; therefore, we use 25 sub-bands in each electrode.

The WPD method tends to induce a large vector set (400 feature vectors), especially when the selected EEG channels increase. Thus, the feature selection process is important to reduce the features set before combining the significant features with the other small-feature vector set. Only 96 features were selected from the WPD feature vectors. Correlation-based feature selection (CFS) is a simple and effective feature selection method which is able to reduce dimensionality without affecting accuracy [25]. CFS is a simple and correlated-based filter algorithm that is applicable in discrete and continuous problems [25]. The CFS algorithm evaluates the feature subset according to correlation-based heuristic merit. It judges the usefulness of a feature through the inter-correlation among the features.

6.3 Classification

Incremental KNN also known as KNN and can be found in WEKA as instance-based learning with parameter *k* (IB*k*) classifier. The knowledge flow interface is an alternative way to the explorer in WEKA. However, only the knowledge flow interface works incrementally.

KNN is a well known classification technique and is an example of instance-based learning technique. It is a supervised learning algorithm and is perceived as a simple and easy-to-use

Table 2 Experimental results and validation test of AUC in three situations

Use case	Technique	Window size = 0	p-Value, 2-tailed	Statistical test	Window size = 1.5[a]	p-Value, 2-tailed	Statistical test
perfect situation	IncFRNN	0.8843	0.009	significantly different	0.8843	0.000	significantly different
	IBk	0.8675			0.7975		
regular situation	IncFRNN	0.8798	0.002	significantly different	0.8723	0.000	significantly different
	IBk	0.8647			0.6862		
challenging situation	IncFRNN	0.8842	0.000	significantly different	0.8818	0.000	significantly different
	IBk	0.8649			0.6869		

[a]1.5 times the number of training objects

algorithm. In KNN, Euclidean distance is used to calculate the distance between training and testing objects. When the nearest distance of the training object has been located, its class will be predicted for the test object, based on the Euclidean distance. The formula to calculate the Euclidean distance of two points is

$$\text{distance}(X_1, X_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2} \tag{3}$$

where $X_1 = (x_{11}, x_{12}, \ldots, x_{1n})$ and $X_2 = (x_{21}, x_{22}, \ldots, x_{2n})$.

The time taken for the classification of the test object increases linearly with the number of training objects. Consequently, it is sometimes necessary to restrict the number of training objects in the training pool by defining the window size threshold [26]. The window size determines the maximum number of objects allowed in the training pool. The addition of new objects greater than the value of the window size will result in old objects being removed.

6.4 Experimental setting and performance measurement

The model learning and validation experiments involving the IncFRNN and IBk techniques were implemented using the WEKA data mining tool. Certain parameters need to be set in order to perform classification in knowledge flow WEKA. The number of k should always be set to an odd value, so that the new incoming object can be easily classified [27]. Yazdani *et al.* [28] tested the parameter k from 1 to 100 and the 5-NN classifier obtained 100% accuracy for person identification. The number of k is set to 5 for the proposed IncFRNN and IBk classifiers. The window size thresholds for the implementation of IncFRNN and IBk techniques were initialised as 0, indicating an unlimited number of objects in the training pool, whereas the window size threshold was defined as 1.5 times the total number of training objects loaded for both the IncFRNN and IBk techniques. A pilot study was carried out to test on 1.5 times and 2 times window size threshold as compared with unlimited window size. There is no significant difference between two times window size and unlimited window size threshold toward classification performance. Thus, two types of windows sizes were used in the experiments, i.e. unlimited number of training objects, and 1.5 times of the existing training objects.

The experimental results were analysed based on accuracy, area under the Receiver Operating Characteristic (ROC) curve (AUC) and Cohen's Kappa. The accuracy evaluates the effectiveness of the classifier by its percentage of correct predictions, whereas the AUC calculates the simple trapezoidal integration, which relates to sensitivity and specificity. The AUC was found to have a more discriminating value and was more statistically consistent compared with class distribution. Cohen's Kappa was used to assess inter-rater reliability when observing qualitative/categorical variables [29]. An Anderson–Darling test in MATLAB was carried out to test the normality distribution of the results. A paired sample t-test was used to validate AUC and Cohen's Kappa results because it was found to be normally distributed. On the other hand, the Wilcoxon signed-rank test was used for accuracy measure since it was found to be not normally distributed.

7 Results and discussion

In this stage, a comparison between two incremental learning techniques (IncFRNN and IBk) was carried out. Both the IncFRNN technique and IBk technique were run incrementally in the knowledge flow WEKA data mining tool. The authentication results were evaluated based on AUC, accuracy and Cohen's Kappa. In addition, a validation test was carried out to test the significance of the difference between two incremental techniques.

7.1 Experimental results and validation test

Table 2 shows the experimental results and validation tests for perfect, regular and challenging situations, based on AUC with different window size thresholds. The window size for IncFRNN and IBk techniques were initialised as 0, which indicates unlimited number of objects in the training pool. Both the IncFRNN and IBk techniques only perform object insertion into the training pool. However, inserting the objects incrementally may lead to a large number of objects in the training pool and it is necessary to restrict the number of objects. Thus, the window size threshold was defined as 1.5 times the number of training objects.

Table 2 shows that both the IncFRNN and IBk techniques yielded good classification results in terms of AUC. The AUC values gained by IncFRNN technique without window size threshold were 0.8843, 0.8798 and 0.8842, whereas the IBk technique obtained 0.8675, 0.8647 and 0.8649 for perfect, regular and challenging situations, respectively. The classification results demonstrate that updating the training pool incrementally improved the authentication performance. Since EEG signals are known to be highly uncertain and non-stationary, it is essential to incrementally reshape and reform the knowledge granules to include new EEG signal patterns resulting from ambient noise to obtain good authentication results in the future.

The size of the training pool can be restricted by defining the window size threshold in both the IncFRNN and IBk techniques. The deletion of an object is performed when it exceeds the window size threshold. The correct predictions decreased when the window size threshold was defined. The AUCs of IncFRNN technique with 1.5 times window size achieved 0.8843, 0.8723 and 0.8818, whereas AUCs of IBk technique were recorded as 0.7975, 0.6862 and 0.6869 for perfect, regular and challenging situations, respectively. The IncFRNN technique showed a slight difference when the window size was defined, whereas IBk technique showed a huge difference when the window size threshold was defined. This is because the strategy on the deletion of object in the IncFRNN technique is different from that for the IBk technique. The deletion of object in the IncFRNN algorithm is based on the frequency counter and within the same class to store the most representative objects and eliminate the rarely used objects. The IncFRNN algorithm was able to learn from different cases and reconstruct personalised knowledge granules, whereas the IBk technique performed object deletion based on FIFO strategy for whole training set. The FIFO strategy was not suitable for biometric authentication modelling due to the dataset having imbalanced class objects. The authentication results in Table 2 show the weakness of the IBk technique when incrementally updating the training pool through the FIFO strategy.

However, the authentication results were the opposite for accuracy measure as shown in Table 3. The validation tests were shown to be significantly different for all the situations. Batch learning using the IBk technique was better than with the proposed

Table 3 Experimental results and validation test of accuracy in three situations

Use case	Technique	Window size = 0	p-Value, 2-tailed	Statistical test	Window size = 1.5[a]	p-Value, 2-tailed	Statistical test
perfect situation	IncFRNN	95.08	0.000	significantly different	95.10	0.000	significantly different
	IB*k*	97.95			97.58		
regular situation	IncFRNN	94.16	0.000	significantly different	94.38	0.000	significantly different
	IB*k*	97.90			97.25		
challenging situation	IncFRNN	94.39	0.000	significantly different	94.51	0.000	significantly different
	IB*k*	97.88			97.25		

[a]1.5 times the number of training objects

Table 4 Validation test of Cohen's Kappa in three situations

Use case	Technique	Window size = 0	p-Value, 2-tailed	Statistical test	Window size = 1.5[a]	p-Value, 2-tailed	Statistical test
perfect situation	IncFRNN	0.3671	0.052	significantly not different	0.3660	0.000	significantly different
	IB*k*	0.4198			0.2553		
regular situation	IncFRNN	0.3200	0.000	significantly different	0.3134	0.000	significantly different
	IB*k*	0.4143			0.1281		
challenging situation	IncFRNN	0.3358	0.001	significantly different	0.3365	0.000	significantly different
	IB*k*	0.4139			0.1296		

[a]1.5 times the number of training objects

IncFRNN technique. The IB*k* technique gained higher True Negative Rate (TNR) (correct prediction on class impostor), but very low True Positive Rate (TPR) (correct prediction on class client). This shows that the high-accuracy rate achieved by the IB*k* technique was largely contributed by TNR. The accuracy results were biased toward the class with a large number of training objects, i.e. the impostor class in the experiment. Owing to the imbalanced class objects, the FIFO strategy in the IB*k* technique will delete all the class clients. Hence, the accuracy was increased by the TNR.

Table 4 shows the validation tests of Cohen's Kappa in three situations. The tests showed IB*k* performed better than IncFRNN technique when no window size threshold was set, mainly because the IB*k* technique obtained higher TNR compared with IncFRNN technique. On the other hand, the Cohen's Kappa was the opposite when a window size threshold was set. This is because the deletion of objects is not suitable for biometric authentication modelling.

Overall, IncFRNN technique is more promising compared with IB*k* technique because of the importance of TPR in biometric authentication modelling.

8 Conclusion

In this paper, we have investigated the performance of incremental learning in handling EEG signals classification for biometric authentication. From the results obtained in this experiment, the IncFRNN technique performed better than the IB*k* technique in terms of AUC. By adding in the heuristic update method, we have successfully proven that the new IncFRNN technique is feasible for brainwave biometric authentication modelling. The proposed heuristic update method aims to update the training pool incrementally, based on the object variation strategy, thus it tends to retain the current characteristics of an individual. The frequently used EEG signal patterns (the current individual characteristics) are retained, whereas the rarely used patterns (the past individual characteristics) are removed. This has critically improved the authentication performance in various data acquisition settings. However, in real practise, it is important to validate the FRNN prediction performance to ensure only correct knowledge is added into the knowledge base. Besides incrementing based on object variation, improvement could be made by incrementally updating the training pool with variation of attributes. Instead of using a fixed number of features before learning process, the algorithm would update the features incrementally from time to time, in order to use relevant features for classification. Hence, the future work will focus on updating the variation of attribute incrementally.

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