Brain prints for biometrics: An introduction and review of current trends

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INTRODUCTION

The field of **biometrics** has received considerable attention from the academic community, technology companies, and by the public. This is mainly due to the multiple security issues caused by alarming number of frauds in banking and internet transactions, threats to national security due to terrorism etc. Biometrics involve the use of behavioral or physiological characteristics where traditionally finger prints have been used as the standard de facto method in biometrics. Alternative biometrics such as those based on signature, face features, palmprint, hand geometry, iris and voice have also been proposed (Wayman et al, 2004). There is also a more recent trend to this where measurements from the heart, brain and shape of inner ear etc that have been suggested either to replace the existing biometrics or to augment them to obtain improved performance (Revett 2012). Because of this trend, it is desirable to present an introduction and review of current trends to serve as a guide to people outside the field. The goal of this article is to present an introduction to biometric technology using electrical patterns from the brain, known as brain prints and discuss the current trends and challenge problems that are likely to shape the field in the near future.

BACKGROUND

Biometrics can be divided into two general categories: **authentication** (which is also known as verification) and **identification**. Authentication involves a process were the user declares his or her identity and the system then searches its stored database for the person's information. If matching template information is obtained using the biometric pattern (up to a certain pre-determined threshold), the output is seen as positive, i.e. the person is verified but otherwise it is negative and the person is classified as impostor and rejected. On the other hand, identification involves matching the biometric patterns from user to the stored databases of a pool of users. This is normally more complicated task as it means matching against numerous user databases instead of one as in the case of verification.

MAIN FOCUS OF THE ARTICLE

Newer types of biometrics

As mentioned, newer research has focused on alternative **biometrics** such as those based on gait (Matovski et al, 2012), face features (Kelkboom et al, 2007), palmprint and hand geometry (Kumar et al, 2003), retina (Jeffers et al, 2012), iris (Melin, 2012) and voice (Gupta and Chatterjee, 2012). The second trend is to use signals from brain (Palaniappan 2006) and heart (Palaniappan and Krishnan, 2004) as biometrics. Such signals from the brain and heart are commonly employed for medical diagnosis but the advantage of using such biological signal based biometrics compared to other biometrics is its distinctiveness, i.e. they are difficult to be duplicated by someone else, therefore not easily forged or stolen. The data collection can be cumbersome though the future improvements will reduce the unwieldiness and the distinctiveness could outweigh the difficulties especially for high security applications. This article will focus on the use of patterns from the brain for both **authentication** and **identification**.

What are brain patterns?

Electrical activity of the brain when recorded on the scalp is commonly known as electroencephalogram (**EEG**). There is also another invasive procedure where the extracted activity is obtained by implanted electrodes and this is known as electrocorticogram (ECoG) but this will not be discussed here as it has no scope for biometrics (only for medical purposes).

The basic functional unit in the brain is the neuron, which is found in the cerebral cortex. Four different areas of the cortex (frontal, parietal, temporal and occipital) are responsible for varying functions, for example the occipital lobe processes visual information and auditory perception is processed in temporal lobe. Figure 1 shows the neuron and its interconnections where the brain is made of billions of such connections. The cell body (soma) of a neuron receives neural activity inputs though dendrites and outputs its neural activity through an axon. A myelin sheath covers the axon and that acts as an insulator (just like rubber covering of copper electrical wires). Ranvier nodes in the axons acts as amplifiers to amplify the signals (Palaniappan, 2010).

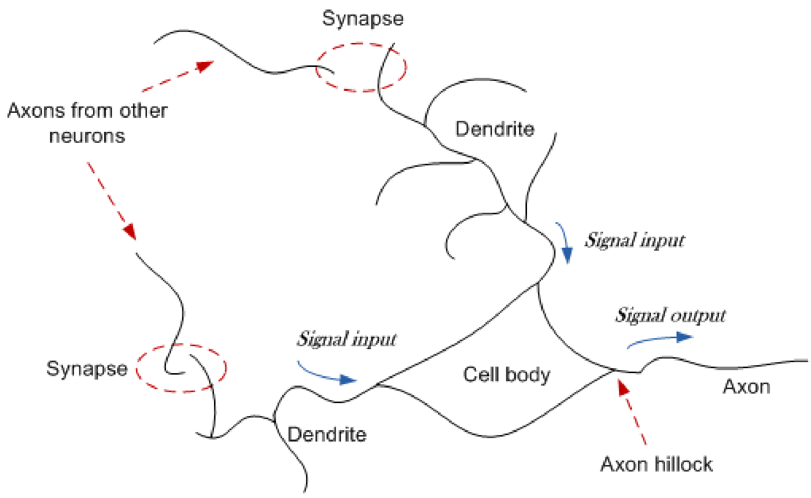


Figure 1. Neuron and its interconnections (Palaniappan, 2010).

As mentioned earlier, this cumulative electrical activity of groups of neurons known as **EEG** activity is recorded through electrodes placed on the scalp. The recorded EEG rhythms can be categorised into five different rhythms based on their frequency ranges (frequency is a measure on the number of cycles):

- Delta (0.5-4 Hz) rhythm. This rhythm appears during deep sleep stages and in infants as irregular activity;
- Theta (4-7 Hz) rhythm which is encountered in early sleep stages and drowsiness;
- Alpha (8-12 Hz) rhythm which is the typical rhythm during relaxed state with eyes closed (it is suppressed with eye opening);
- Beta (13-30 Hz) rhythm which is prominent during stressful situations;
- Gamma (> 30 Hz) rhythms, which are believed to be involved in higher order functions of the brain such as feature binding of a perceived image.

An **EEG** cap, which normally consists of 16, 32 or 64 (though 128 or 256 is also possible) electrodes is used to record the brain patterns. Figure 2 shows a commonly used 10-20 electrode placement system (Jasper, 1958). To increase the conductance between the scalp and the electrodes, water based gel is commonly used (though dry electrodes are becoming more common now). The EEG electrical signals are in the microVolts range (i.e. very small amplitude) and require amplification and conversion to digital using a converter. These digital signals are normally passed to a preprocessing module that reduces noise by performing frequency specific filtering.

Figure 3 shows an example of a noisy and cleaned **visual evoked potential** (VEP, a type of EEG evoked during visual stimulus perception). This is then followed by feature extraction module that obtains features representative of the signal through a specifically developed model. Next, a classifier such as artificial neural network is frequently employed to recognise or verify the person's identity.

The final step would be a control stage where after identifying/verifying himself/herself correctly, the user can then be allowed to proceed to the application stage, i.e. perhaps open a secured door, access confidential files etc.

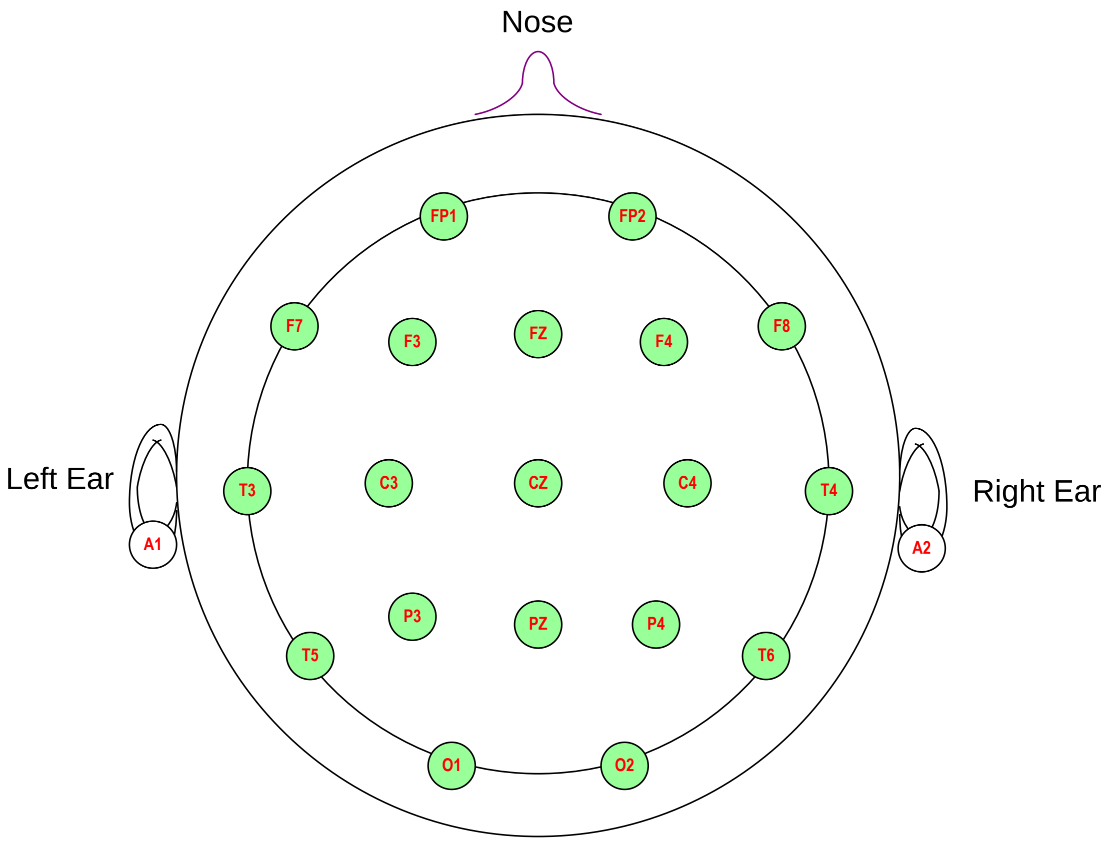
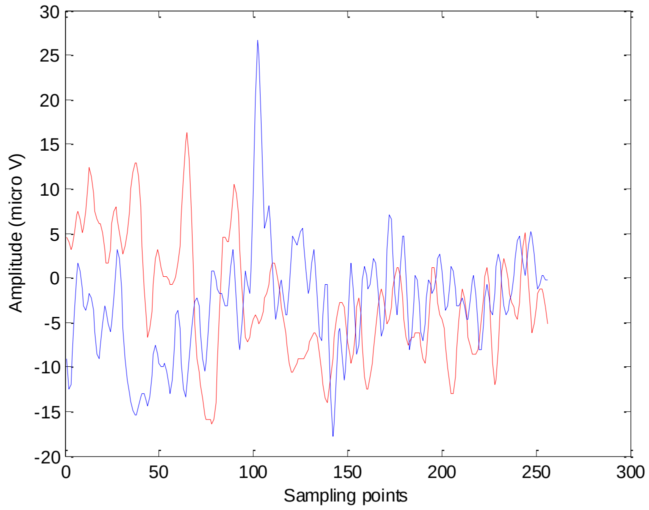
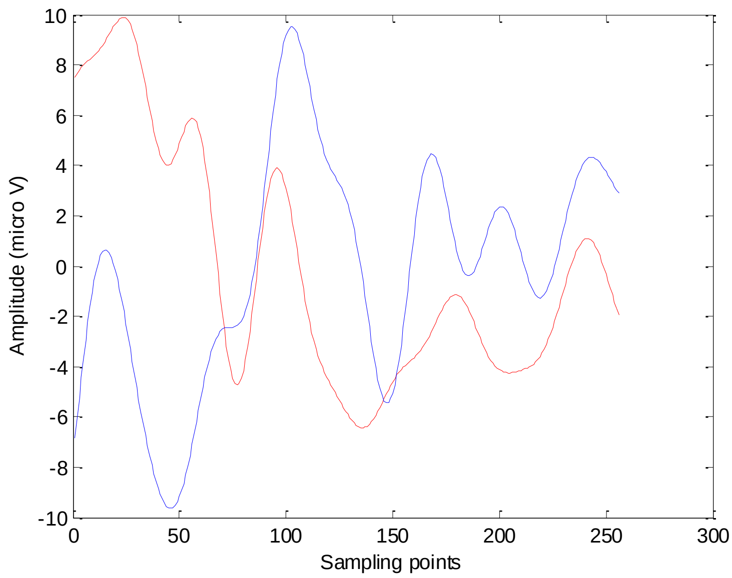


Figure 2. EEG electrode location on the scalp (10-20 channel system (Jasper 1958) is shown here as an example where A1 and A2 are reference electrodes).



(a)



(b)

Figure 3 (a) Noisy VEP and (b) cleaned VEP.

Identification using brain prints

In general, brain prints are unique to each individual. However, as the recorded signal is very noisy, algorithms to pre-process and extract suitable features are not trivial. The authors (Palaniappan and Mandic, 2007) have proposed using VEP signals obtained during visual perception of commonly encountered black and white line objects such as car, book, pen etc. Upon perceiving these objects, the brain starts to process these, where higher order functions such as extracting details of the object and matching to memory takes place in order to recognise the object. Such higher order processes can be detected in gamma band frequency range of **EEG** (Basar et al, 1995). Gamma band appears in EEG whenever the brain does complex processing and is absent when there is no deep processing involved. For example, patients in vegetative state would not have EEG in gamma band range, though they may have EEG in other frequency ranges. Gamma band generally denotes frequency range above 30 Hz though a wider range of 20-50 Hz was used in (Palaniappan and Mandic, 2007). Other previous research studies have shown that EEG in alpha and beta could have a link to individuality (Buchbaum and Gershon, 1978, Plomin, 1990) while the work in (Palaniappan and Mandic, 2007) focused on gamma band.

Energy in gamma band was obtained from 61 active channels and Davies Bouldin index (Davies and Bouldin, 1979) was used to reduce the number of features. Elman neural network (Elman, 1990) was used to classify the features into categories representing the subject. The results showed that using a single channel gave very poor results but using multiple channels could give accuracy of 99% when tested on 40 subjects. This indicated that the distinctiveness between each subject was given by the overall pattern of thoughts in different areas of the brain and a single process focused on certain area of the brain will not be sufficient to discriminate individuals.

In another study (Jian-Feng, 2010), the author studied brain prints obtained during motor imagery, i.e. when subjects imagine moving a certain part of their body. The imagined movements studied were left hand, right hand, foot and tongue. A number of single channel features such as auto-regressive, linear complexity, energy spectrum density and energy entropy were studied. In addition, relationship between two-channels was used as features and this included phase locking value, mutual information and cross correlation. However, such methods based on motor imagery suffer from two major pitfall: one, it takes very long (in the order of a few seconds to successfully identify the motor imagery) and secondly, training stage of many sessions (to train the user to successfully imagine the movements) is required which is sometimes not possible in biometrics.

Poulus et al (2002) studied the **identification** of persons using both linear and nonlinear methods of processing EEG. Specifically, they studied autoregressive features as linear and bilinear autoregressive moving average model as nonlinear features where a learning vector quantiser was used as the classifier. EEG signals were recorded for 3 seconds and a number of test cases were performed. Since it was a pilot study, the results were not sufficiently satisfactory for biometric purposes.

Authentication using brain prints

Brain prints can also be used to verify the identity of a user. In this scenario, the system either accepts the user claiming a given identity or rejects his or her claim. The user is called as **client** in the former case and as impostor as in the latter case. In such systems, there will be two types of errors: false accept error (FAE) or false reject error (FRE). The former is the error made by the system when wrongly accepting an impostor while the latter is the error made when wrongly rejecting the client.

This **authentication** using brain patterns was studied in (Palaniappan 2008) where the author applied a two stage procedure. The **EEG** was obtained while the subjects were thinking of different mental tasks. The idea was based on the fact that different individuals have a different approach in executing mental tasks. Several different mental tasks (Keirn and Aunon, 1990) were used:

- **Baseline task,** where the subjects were asked to relax and think of nothing in particular.
- **Non-trivial mathematical task** where the subjects were given nontrivial multiplication problems, such as 42 times 89, and were asked to solve them without vocalising or making any other physical movements.
- **Geometric figure rotation task** where a particular three-dimensional block object was shown for 30 seconds and subjects visualise the object being rotated about an axis.
- **Mental letter composing task** where the subjects were asked to mentally compose a letter to a relative or a friend without vocalising.
- **Visual counting task** where the subjects imagine a blackboard and visualise numbers being written on the board sequentially, with the previous number being erased before the next number is written.

These tasks were shown as they generate interhemispheric asymmetry pattern in **EEG** signals. Data from six channels (electrodes) were used: C3, C4, P3, P4, O1 and O2 (C stands for central location, P for parietal location and O for occipitial location) and several methods such as autoregressive coefficients, channel spectral powers, inter-hemispheric channel spectral power differences, inter-hemispheric channel linear complexity and non-linear complexity (approximate entropy) were used as EEG features and cross validated using Manhattan distance measures.

The **authentication** approach was unique here as it was based on a novel two-stage method where both **false accept error** (FAE) and **false reject error** (FRE) rates were minimised (as shown in Figure 4). In most biometric studies, an equal error rate (EER) is found which is the intersection of FAE and FRE curves (which means one is minimised at the expense of the other). Perfect accuracy was obtained, i.e. the FRE and FAE were both zero when the proposed method was tested on five subjects using a combination of the above mental tasks.

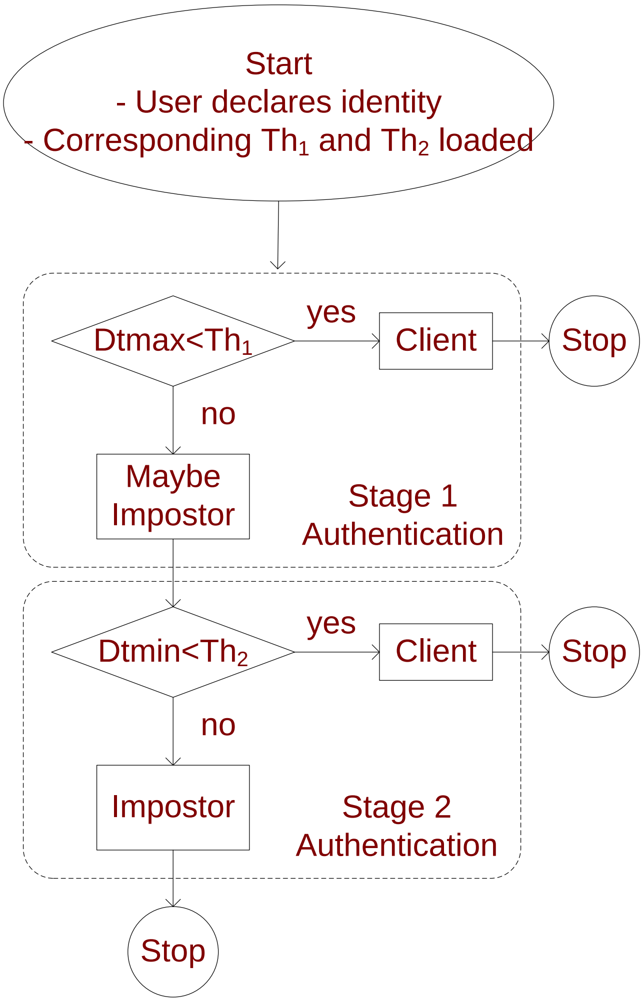


Figure 4: Two-stage verification system (Palaniappan, 2008) where different thresholds (Th1 and Th2) were used to decrease the FAE rate while also minimising FRE rate.

Pass code generation with brain prints

Brain responses can also be used to generate a pass code or personal **identification** number (PIN) instead of identifying or **authentication** a person's identity for example, in automated teller (ATM) machines. Such methods are largely based on brain-computer interface (BCI) paradigms such as P300 BCI (Gupta et al, 2009)

The authors in the studies in (Gupta et al, 2008, Gupta and Palaniappan, 2009) explored the use of a sequence of colours as pass code where the subject focuses on colours that randomly flash on screen. For example, a passcode could be in the form of GREEN, GREEN, BLACK, BLUE, BLACK - the sequence is obviously important and the length can be increased for added security. So, instead of typing the pass code, the pass code here is generated by thought alone. The colour flashes in the study lasted 100 ms, which is sufficient for the brain to recognise the colour and match it with the pass code colour in the memory.

There is a specific response that occurs in the brain around 300 ms after the stimulus onset when the colour thought by the user flashes and this component is absent when non pass code colours (i.e. non-focused target) flash on screen. An example of this brain response is shown in Figure 3 (b) where the blue line shows the response from a target colour while the red line is from a non-target colour and it can be seen that the response is higher around 300 ms (which is around sampling point 100) for the target response. Advanced signal processing algorithms were employed to detect this response and through it the colour focused in the mind of the subject can be detected. The process is repeated until the required sequence of colours is obtained. The advantage of using thoughts here is that *shoulder surfing* problem is avoided, so the user not worry about people peeping over the shoulder to steal the pass code. But the measure also shares a similar problem to other pass code mechanisms where one could *steal* the pass code through force (for example, by threatening with a knife).

Figure 5: A subject uses the pass code system where alphanumeric characters were generated from thoughts.

A similar study was performed in (Gupta et al, 2012) that explored the use of numbers and obviously this would be useful for PIN generation using thoughts. Perfect accuracies were obtained for most of the subjects tested though several trials were required.

Flashing visual stimulus can sometimes lead to issues such as epilepsy so auditory tones were studied for biometric purpose by Gupta and Palaniappan, 2012 where the brain responses were used to decide the tones focused by the user. Obviously, such audio based system would prove to be more fraud resistant than visual based systems. But the accuracy using audio tones were reported to be lower than visual stimulus as users find it more difficult to concentrate on specific audio tones as compared to focusing on visual objects.

FUTURE RESEARCH DIRECTIONS

Biometrics based on thoughts is still in infancy and there are still many challenges that need to be addressed before the technology becomes viable for commercialisation:

- **Gel based electrode technology:** To increase the conductance between the electrode and scalp, most systems still use water based gel. This is required as **EEG** signals generated in the brain pass through skull and scalp that attenuates the signal and hence sufficient contact is necessary to obtain good quality signal. There are however some recent advances in electrode technology that holds a chip that reduces noise on the signal itself but such electrodes still require gel. The dry electrode technology based on capacitance and hair-like pin structures have started emerging but the performance of such electrodes is only good in constraint laboratory environments (Gtec, 2012).
- **Multiple channels:** Many of the brain response based biometric technology achieve good accuracy only when multiple channels are used. Not only this increases the cost but also the set-up time is increased especially with gel based electrodes. A recent work (Palaniappan et al, 2011) has explored the use of a single channel but still achieving good accuracy through advanced signal processing but the issue was whether such technology would still work over a period of time.
- **Stability:** Stability of such patterns over time is questionable as the brain is constantly evolving by acquiring new knowledge. The study by Palaniappan and Revett (in press) has shown that brain patterns do change over time though the use of multiple channels can reduce the variability. Therefore, future studies should be

directed to develop suitable normalisation factors to avoid genuine users from being rejected by the system after a lapse of time.

CONCLUSION

The numerous studies in this topic show that brain patterns have promise for being used as biometric as there are patterns that are unique to each individual. This article has given an introduction to the currently emerging biometric technology based on brain prints for biometric **authentication** and **identification** and on pass code generation using thoughts.

Obviously, the use of electrode caps causes unwieldiness and such applications would be more useful for verifying small groups of people, where the security would be an utmost important issue such as access to classified confidential documents or entry to restricted areas. The main issue with other biometric technology is forgery but the thought processes in the brain are difficult to be duplicated and hence, brain prints will have higher fraud resistance. Nevertheless, this discussion applies to fraud in the data collection (sensor level) step and not fraud in the other parts of the system such as decision making, which has the possibility of fraud for any biometric.

Overall, the current advances in the related technologies indicate that it is highly likely that biometric technologies based on brain prints will be a reality very soon.

References

[1] Wayman, J, Jain, A., Maltoni, D., & Maio, D. (eds.) (2004). *Biometrics Systems: Technology, Design and Performance Evaluation*, Springer-Verlag, New York.

[2] Revett, K. (2012). Cognitive biometrics: a novel approach to person authentication. *International Journal of Cognitive Biometrics*, 1(1), 1– 9.

[3] Matovski, D., Nixon, M., Mahmoodi, S., & Carter, J. (2012). The effect of time on gait recognition Performance. *IEEE Transactions on Information Forensics and Security*, 7(2), 543-552.

[4] Kelkboom, E. J. C., Gökberk, B., Kevenaar, T. A. M., Akkermans, A. H. M., & van der Veen, M. (2007). 3D Face: Biometric template protection for 3D face recognition. *Advances in Biometrics*, *Lecture Notes in Computer Science*, 4642, 566-573.

[5] Kumar, A., Wong, D.C.M, Shen, H.C., & Jain, A.K. (2003). Personal verification using palmprint and hand geometry biometric audio- and video-based biometric person authentication, *Lecture Notes in Computer Science,* 2688, 668-678

[6] Jeffers, J., Davis, S.A., & Horadam, K.J., Estimating individuality in feature point based retina

templates. (2012). *5th IAPR International Conference on Biometrics (ICB)*, 454-459.

[7] Patricia, M. Neural network optimization for the recognition of persons using the iris biometric measure (2012). *Modular Neural Networks and Type-2 Fuzzy Systems for Pattern Recognition Studies in Computational Intelligence,* 389, 163-184.

[8] Gupta, S., & Chatterjee, S. (2012). Text dependent voice based biometric authentication system using spectrum analysis and image acquisition. *Advances in Computer Science, Engineering & Applications, Advances in Intelligent and Soft Computing*, 166, 61-70.

[9] Palaniappan, R. (2006). Electroencephalogram signals from imagined activities: A novel biometric identifier for a small population. In Corchado E. et al. (eds): Intelligent Data Engineering and Automated Learning – IDEAL 2006, *Lecture Notes in Computer Science*, 4224, 604-611.

[10] Palaniappan, R. & Krishnan, S. M. (2004). Identifying individuals using ECG signals. *Proceedings of International Conference on Signal Processing and Communications*, 569-572.

[11] Palaniappan, R. (2010). *Biological Signal Analysis*. Ventus Publishing, Denmark.

[12] Jasper, H. (1958). The ten twenty electrode system of the international federation. *Electroencephalographic and Clinical Neurophysiology,* 10, 371-375.

[13] Palaniappan, R. & Mandic, D.P. (2007). EEG based biometric framework for automatic identity identification. *International Journal of VLSI Signal Processing Systems for Signal, Image and Video Technology (special issue on Data Fusion for Medical, Industrial, and Environmental Applications)*, 49 (2), 243-250.

[14] Basar, E., Eroglu, C.B., Demiralp, T., & Schurman, M. (1995). Time and frequency analysis of the brain's distributed gamma-band system. *IEEE Engineering in Medicine and Biology Magazine,* 400-410.

[15] Buchbaum M. S. & Gershon, E.S. (1978). Genetic factors in EEG, sleep and evoked potentials. In Davidson (ed): *Human consciousness and its transformations*, Phenomen Press, 1978.

[16] Plomin R. (1990). The role of inheritance in behavior. Science, 248: 183-188.

[17] Davies D.L. & Bouldin D.W. (1979). A cluster separation measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1(4), 224-227.

[18] Elman, J. L. (1990). Finding structure in time. *Cognitive Science*, 14, 179-211.

[19] Jian-feng, H. (2010). Biometric system based on EEG signals by feature combination, *Proceedings of International Conference on Measuring Technology and Mechatronics Automation*, 752 – 755.

[20] Poulos, M., Rangousi, M., Alexandris, N., & Evangelou. A. (2002). Person identification from the EEG using nonlinear signal classification. *Methods of Information in Medicine*, 41, 64-75.

[21] Palaniappan, R. (2008). Two-stage biometric authentication method using thought activity brain waves. *International Journal of Neural Systems*, 18(1), pp.59-66.

[22] Keirn, Z. A. & Aunon, J. I. (1990). A new mode of communication between man and his surroundings. *IEEE Transactions on Biomedical Engineering*, 37 (12), 1209-1214.

[23] Gupta, C. N., Khan, Y.U., Palaniappan, R. & Sepulveda, F. (2009). Wavelet framework for improved target detection in oddball paradigms using P300 and gamma band analysis. *Special issue on Bio-signals: Data Acquisition, Processing and Control, International Journal of Biomedical Soft-computing and Human Sciences*, 14(2), 61-67.

[24] Gupta, C. N., Wilson, J. J., Palaniappan, R. & Syan, C. S. (2008). Single trial P300 amplitude for pass-code brain-machine interface design. *CD Proceedings of International Conference on Advanced Computing*.

[25] Gupta C.N. & Palaniappan, R. (2009). Biometric paradigm using visual evoked potential. In Khosrow-Pour, M. (ed.): *Encyclopedia of Information Science and Technology, 2nd ed.*, IGI Global, 1, 362-368.

[26] Gupta, C. N., Palaniappan, R., & Paramesran, R. (2012). Exploiting the P300 paradigm for cognitive biometrics. *International Journal of Cognitive Biometrics*, 1 (1), 26-38.

[27] Gupta C. N. & Palaniappan, R. (2012). Using high-frequency electroencephalogram in visual and auditory-based brain-computer interface designs. *EContact! — Biotechnological Performance Practice*, Canadian Electroacoustic Society, 14.3.

[28] Gtec, (2012). http://www.gtec.at. Accessed 28 November 2012.

[29] Palaniappan, R. Gosalia, J. Revett K., & Samraj, A., (2011). PIN generation using single channel EEG biometric. In Abraham et al. (eds): *Springer in Communications in Computer and Information Science Series*, 193(IV), 378-385.

[30] Palaniappan R. & Revett, K. (in press). PIN generation using EEG: A stability study. *International Journal of Cognitive Biometrics*.

KEY TERMS AND DEFINITIONS

- Auditory evoked potential (AEP): A type of EEG that is evoked upon the presentation of an auditory (sound) stimulus.
- Authentication or verification: A procedure to verify or authenticate a user based on the claims of the user.
- Biometrics: A field of study that attempts to verify or identify human beings using their intrinsic physical or behavioural traits.
- Client: the actual user claiming the identity.
- Delta, theta, alpha, beta, gamma: some commonly used spectral bands in EEG.
- Electroencephalogram (EEG): A measurement of the electrical activity of the brain in microVolts recorded from electrodes placed on the scalp.
- False Accept Error (FAE): one of the two types of errors used in authentication. It is the error made by the system when it wrongly accepts impostors as clients.
- False Reject Error (FRE): it is the error made by the system when it wrongly rejects the clients as impostors.
- Identification: A procedure to identify a user's identity from a pool of users.
- Impostors: user trying to forge another person's identity.

- Visual evoked potential (VEP): Similar to AEP but evoked upon the presentation of a visual stimulus.