IOP Conference Series: Materials Science and Engineering

PAPER • OPEN ACCESS

Lack of knowledge matching algorithms using distance measurements on brainwave features

To cite this article: A Azhari and DP Ismi 2018 IOP Conf. Ser.: Mater. Sci. Eng. 403 012080

View the article online for updates and enhancements.

Lack of knowledge matching algorithms using distance measurements on brainwave features

A Azhari¹ and DP Ismi²

^{1,2}Informatics Department, Universitas Ahmad Dahlan, Yogyakarta, Indonesia.

¹ahmad.azhari@tif.uad.ac.id, ²dewi.ismi@tif.uad.ac.id

Abstract. All human activities are controlled centrally through the brain. The brain produces electrical forces that transmit information between neurons that are represented in wave form. Brainwaves can be used as a medium for identifying and authenticating users because individual brain waves are different and have distinctive characteristics. Characteristics of brainwaves can be triggered using a pattern that is protruding and constant. The application of cognitive tasks developed based on the incorporation of human perceptions and psychological characteristics can serve as a stimulus. Feature extraction is done by applying statistics in the form of mean value, standard deviation, skewness, kurtosis, and entropy. These features are analyzed and compared using a distance measurement matching algorithm. The results obtained from this test indicate that the Minkowski algorithm is capable of providing optimal results in data matching.

1. Introduction

Biometrics is a method used to recognize humans based on the size of physiological characteristics and human behavior [1]–[7]. The use of Biometrics to recognize a person is widely used in previous studies [5],[6],[8]–[19]. A person's face has been used for recognition, both for recognizers and unrecognized. A person's voice can also be recognized without seeing the person directly. Step motion or gesture of a person can also be recognized from the way it goes. Physiological characteristics using the physical parts of a person's body include fingerprint, face image, hand vessels, retina, iris, palms, teeth and body odor / sweat. While the introduction based on behavioral characteristics using one's behavior include gesture, signature, and sound [3],[4],[20].

There are six biometrics commonly used for self-recognition systems, including: fingerprint, iris, face, voice, hand geometry, and signature [3]. The latest development of the field of biometrics is cognitive biometrics based on specific responses of the human brain, including: brainwaves, odors, and face monitors [4],[5].

The purpose of application of Biometrics is to identify and verify human characteristics [1]. The verification system aims to accept or deny an identity claimed by a person, while the identification system aims to resolve a person's identity [2],[5],[6],[20],[21]. Various approaches have been developed for self-introduction. The approaches can basically be grouped into three, namely: first, based on possessions-based, such as keys (physical keys) and cards. Second, based on knowledge-based, such as user identity, PIN, and password, and third, biometrics (biometrics-based), such as fingerprint, face, sound, and so on [1],[3],[4],[17]. Advantages of biometrics system that uses attributes attached to the body (something what you are) and attributes attached to the behavior of

someone (something what you do). This advantage can reduce duplication, shared, and forgotten usage as it has in traditional recognition systems [3],[5],[7], [20]–[22].

To get a specific response from the human brain needed a trigger. Reference [1],[5],[17] mentions that the characteristics of brainwaves become very strong when a person is exposed to specific stimuli. In cognitive biometrics, stimuli can be derived from the human cognitive aspect. To record and measure the brainwave activity required electroencephalogram.

Electroencephalogram (EEG) is one of the biomedical instruments that function to obtain, process, and display the wave activity generated by the brain in the form of electrical potential, with a small electrical voltage. By using EEG, brainwave activity can be analyzed to find different work levels in each part of the brain [1],[6],[7],[16],[17].

2. Related Work

Reference [7] using EEG features to authenticate user on biometrics systems. The issues raised are about Vulnerabilities threatening user in Authentication. This study used Common Spatial Patterns (CSP) Values as Main Features and Linear Discriminant Analysis (LDA) as Classification algorithm for set of user data. EEG data used wirelessly improvement accuracy can be expected by avoiding electrodes. The result showed that Beta Band is the most suitable band for imagination and active thinking with 90,91% accuracy better than Alpha Band with 81,81% accuracy. Combination of Both Band (Alpha and Beta Band) showed better accuracy than individual frequency band with 96.96% Accuracy.

Reference [17] proposed feature extraction using cross-correlation method to find specific characteristics of short-wave signals applied specifically to assist patients with disorder neuromuscular channel, in moving the wheelchair to turn right and turn left. The cross-correlation is done by finding the average of the maximum peak point and the minimum peak point coming from the correlation signal. The characteristic of the signal used as a reference to make a special short-wave is the signal feature that has the lowest correlation coefficient. The lowest correlation coefficient of the signal characteristic pair indicates the greatest difference between the signal pair turning right and left turns. The matching used in each signal characteristic is the curve fitting method. The average accuracy at the testing phase of 22 participants for 4 types of movement showed a similar average of 76% for right turn movement, 76% for left turn movement, 74% for right turning imagination and 72% for left-handed imagination.

Reference [5] conducted a study which aims to classify Brainwaves feature using K-Means clustering. EEG single-sensor is utilizing in this study. Several feature statistics such as mean, standard deviation, skewness, kurtosis, and entropy use as a EEG feature. Cognitive activity divided into activity of right brain and the left brain (so-called cognitive task). Cognitive task shows different cluster based on two times test on mathematical activities. This study showed that signal characteristic based on math activity can be used as basic for BCI (brain-computer interface) applications development.

3. Methodology

Data collection is conducted through biometric data acquisition method retrieved from some people. Data collection was collected by applying an EEG single-sensor headset, named NeuroSky Mindset. EEG Electrodes are placed by applying 10-20 placement electrode system [23], right above the FP1 (frontal temporal) or frontal lobe position. EEG retrieval process is done gradually and separately obtained from 6 subjects. Each subject performed two times data retrieval by doing some cognitive task assigned. EEG retrieval process generate 2,560 data along for 20 seconds using sampling frequency of 128 Hz per second. EEG signals are generated by applying stimulus of cognitive tasks. Nine type of EEG stimulus of cognitive task include breath color, face, fingers, counting, objects, pass-thought, singing, and sports.

Based on previous research [13],[19],[24],[25], cognitive task stimulus retrieve by applying several psychological perceptions to get a natural responses of the brain. The nine types of cognitive task are described on Table 1.

Category	Task	Description
Cognitive	Breathing Task (Breath)	Subject focuses on breathing for 20 seconds.
	Object Counting Color Task (Color)	Subjects are asked to remember the color which appears alternately for 20 seconds.
	Mathematical Task (Math)	Subjects are asked to focus on calculating a simple two- numbered multiplication for 20 seconds. False and True answers are ignored in this task.
	Song Recitation Task (Song)	Subjects are asked to imagine a song or sound with lyrics.
Imaginative	Simulated Movement Finger (Finger)	Subjects are asked to focus on simulating by moving a finger without for 20 seconds.
	Simulated Facial Reconstruction (Face)	Subjects are asked to focus reconstructs a person's face for 20 seconds.
	Simulated Object Reconstruction (Object)	Subjects are asked to focus reconstructs the object for 20 seconds.
	Simulated Sport Task (Sport)	Subjects are asked to imagine the exercise movement for 20 seconds.
	Simulated Password Recall Task (Pass-thought)	Subjects are asked to imagine the sentence of password provided for 10 seconds.

Table 1. Nine types of cognitive tag	sk
---	----

In terms of signal processing, biometric data is obtained from data acquisition. Data separately will be grouped into 4 category including subject, cognitive task, and time data retrieval. Furthermore, the feature data will be extract to get difference characteristics that represent unique characteristics of the signal. Feature extraction retrieve from by performing mean, standard deviation skewness, kurtosis, and entropy.

Mean measure of data distribution, standard deviation measures variations of data distribution, skewness measures the asymmetric level of data distribution, kurtosis measures how flat or high the distribution of data is to a normal distribution, and entropy is used to measure the randomness of the data distribution. If mean (\bar{x}) , standard deviation (σ) , skewness (s), kurtosis (k), entropy (H) has the sum of data N and x_i is data *i* then all data can be calculated by equation (1-5).

$$mean = \bar{x} = \frac{1}{N} \sum_{i=0}^{N} x_i \tag{1}$$

standard deviation =
$$\sigma = \sqrt{\frac{1}{(N-1)} \sum_{i=0}^{N} (x_i - \bar{x})^2}$$
 (2)

skewness =
$$s = \sum_{i=0}^{N} (x_i - \bar{x})^3 / (N\sigma^3)$$
 (3)

$$kurtosis = k = \sum_{i=0}^{N} (x_i - \bar{x})^4 / (N\sigma^4)$$
(4)

$$entropy = H = E[-log_2 P(x)] = -\sum_{i=0}^{N} P(x) log_2 P(x) bits$$
(5)

Figure 1 shows the general procedure of proposed method. Data from feature extraction will be normalized before matching algorithm. Matching algorithm using distance measurement. The smallest value of each distance measurement method will be selected and then using the calculation score will be selected the largest value.



Figure 1. General Procedure of Proposed Method

3.1. Euclidean Distance

Euclidean Distance is the most commonly used metric for calculating the similarity of two vectors. Euclidean distance calculates the root of the square of the difference of two vectors. Euclidean Distance using formula (6).

$$d_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}$$
(6)

The smaller d_{ij} score the more similar the two vector features are matched. Conversely, the greater d_{ij} score the more different the two character traits. The nature of the Euclidean distance is that the result is in the range of $0 \le d \le 1$. Notice that the Euclidean distance is a special case of the Minkowski metric, where $\lambda = 2$.

3.2. City Block / Manhattan Distance

Manhattan distance calculates the value of the absolute difference of the two vectors. Manhattan distance using formula (7).

$$d_{ij} = \sum_{k=1}^{n} |x_{ik} - x_{jk}|$$
(7)

3.3. Chebyshev Distance

Chebyshev distance is also called the maximum value distance that serves to check an absolute magnitude of two vector difference. From each value of difference will be selected the greatest value to be made Chebyshev distance. Distance Chebyshev distance using formula (8).

$$d_{ij} = \max|x_{ik} - x_{jk}| \tag{8}$$

3.4. Minkowski Distance

This Minkowski distance with the λ generalize some of the previous metrics, where $\lambda = 1$ is expressed as the distance of City Block and $\lambda = 2$ is expressed by Euclidean distance. Chebyshev distance is a special case of Minkowski distance with $\lambda = \infty$ (infinity) using formula (9).

$$d_{ij} = \sqrt[\lambda]{\sum_{k=1}^{n} |x_{ik} - x_{jk}|^{\lambda}}$$
(9)

3.5. Canberra Distance

For each value of the two vectors to be matched, the Canberra distance divides the absolute difference of two values by the sum of the absolute two values. The results of each of the two matching values are then summed to gain distance to Canberra. If the two coordinates are zero-zero, then defined by 0/0 = 0. This distance is very sensitive to slight changes with the two coordinates close to zero. Distance Canberra using formula (10):

$$d_{ij} = \sum_{k=1}^{n} \frac{|x_{ik} - x_{jk}|}{|x_{ik}| + |x_{jk}|}$$
(10)

3.6. K-Nearest Neighbors

The next stage after the EEG signal performs feature extraction and dimensional reduction that is classified by K-Nearest Neighbour (KNN) classification method. The KNN data sample is based on distance measurement with the number of patterns stored in memory. Testing data was calculated to each training data using distance method the smallest distance of training data to its testing was assumed the correct class.

In the training phase, the algorithm is just doing the feature vector storage and classification of training sample. In the classification phase, the same features are calculated for testing data. The distance from the new vector of the entire sample training vectors are calculated and the amount of the closest k taken.

The way to calculate the KNN algorithm:

• Determining *k* parameter (the number of nearest neighbors)

- Calculate the distance Euclidean distance of each object on the data samples provided
- Sort the objects into groups that have the smallest distance.

3.7. Similiarity Measure

The decision-making process will use the formula (11). The higher the score obtained then it can be assumed that the task will be more dominant.

$$Score = (1 - d_{ij})/2 \tag{11}$$

4. Results

EEG data acquisition results will be extracted to generate the feature. Feature extraction results are obtained using statistical features. Statistical features used are mean values, standard deviation values, skewness values, kurtosis values, and entropy values. These features are grouped according to three categories: subject, cognitive task, and data retrieval time.

Furthermore, Matching features using distance measurement methods. Among the matching methods used were Euclidean distance, Manhattan distance, Chebyshev distance, Minkowski distance, and Canberra distance shown in Table 2 - Table 6.

	Subject_1	Subject_2	Subject_3	Subject_4	Subject_5	Subject_6
Breath	0,29	0,17	0,08	0,01	0,02	0,01
Color	0,06	0,11	0,20	0,01	0,02	0,02
Face	0,02	0,24	0,16	0,02	0,02	0,11
Finger	0,03	0,04	0,03	0,04	0,02	0,01
Math	0,34	0,10	0,70	0,02	0,19	0,03
Object	0,03	0,02	0,10	0,05	0,05	0,00
Pass-thought	0,03	0,02	0,06	0,03	0,01	0,01
Sing	0,01	0,02	0,04	0,08	0,03	0,05
Sport	0,02	0,09	0,13	0,01	0,06	0,01

Table 2. Euclidean Distance

Table 3. Manhattan Distance

	Subject_1	Subject_2	Subject_3	Subject_4	Subject_5	Subject_6
Breath	0,42	0,24	0,13	0,02	0,03	0,02
Color	0,10	0,19	0,29	0,02	0,03	0,02
Face	0,03	0,34	0,21	0,04	0,03	0,14
Finger	0,06	0,06	0,04	0,07	0,03	0,01
Math	0,44	0,15	1,05	0,03	0,27	0,05
Object	0,04	0,04	0,20	0,08	0,08	0,01
Pass-thought	0,04	0,03	0,08	0,04	0,03	0,02
Sing	0,01	0,03	0,06	0,14	0,04	0,09
Sport	0,03	0,15	0,19	0,02	0,10	0,02

	Subject_1	Subject_2	Subject_3	Subject_4	Subject_5	Subject_6
Breath	0,23	0,14	0,07	0,07	0,01	0,01
Color	0,05	0,08	0,18	0,18	0,01	0,01
Face	0,01	0,19	0,16	0,16	0,02	0,10
Finger	0,03	0,04	0,02	0,02	0,02	0,01
Math	0,33	0,10	0,52	0,52	0,14	0,02
Object	0,02	0,02	0,08	0,08	0,05	0,00
Pass-thought	0,02	0,01	0,05	0,05	0,01	0,01
Sing	0,01	0,02	0,04	0,04	0,03	0,04
Sport	0,02	0,08	0,11	0,11	0,04	0,01

Table 4. Chebyshev Distance

Table 5. Minkowski Distance

	Subject_1	Subject_2	Subject_3	Subject_4	Subject_5	Subject_6
Breath	0,26	0,15	0,07	0,01	0,01	0,01
Color	0,05	0,10	0,19	0,01	0,01	0,01
Face	0,01	0,22	0,16	0,02	0,02	0,10
Finger	0,03	0,04	0,02	0,04	0,02	0,01
Math	0,33	0,10	0,62	0,02	0,17	0,03
Object	0,02	0,02	0,09	0,04	0,05	0,00
Pass-thought	0,03	0,01	0,06	0,03	0,01	0,01
Sing	0,01	0,02	0,04	0,07	0,03	0,05
Sport	0,02	0,08	0,11	0,01	0,05	0,01

Table 6. Canberra Distance

	Subject_1	Subject_2	Subject_3	Subject_4	Subject_5	Subject_6
Breath	1,34	1,87	0,89	0,27	0,54	0,10
Color	2,10	2,26	1,52	0,12	1,18	0,22
Face	2,10	2,04	1,43	0,27	1,13	0,90
Finger	1,62	2,04	0,29	1,19	1,08	0,10
Math	2,31	1,23	1,45	0,19	1,67	1,27
Object	2,20	0,87	0,98	0,69	1,16	0,08
Pass-thought	1,94	0,84	1,18	0,55	0,69	0,15
Sing	2,02	1,46	0,74	0,90	1,11	0,83
Sport	0,42	2,15	0,88	1,12	0,88	0,36

The next step, based on distance measurement using several methods, is to take the mean value of each distance measurement result. The data with the mean value are then grouped into one table and made a comparison. Comparison is done by using the threshold value. The threshold value determines

the matching success rate. The threshold value is set based on the smallest value of the overall value in the table. Using KNN classification method, take the smallest value using range $0 \le d \le 1$. Table 7 shows the comparison results between the matching algorithm based on the mean value.

Task	Euclidean	Manhattan	Chebyshev	Minkowski	Canberra	Threshold
Breath	0,0960	0,1429	0,0908	0,0869	0,9850	0,0869
Color	0,0700	0,1089	0,0867	0,0635	1,1900	0,0635
Face	0,0946	0,1309	0,1081	0,0885	1,1850	0,0885
Finger	0,0286	0,0439	0,0240	0,0268	1,0700	0,0240
Math	0,2296	0,3343	0,2717	0,2100	1,2500	0,2100
Object	0,0418	0,0735	0,0407	0,0369	1,1400	0,0369
Pass-thought	0,0266	0,0417	0,0281	0,0245	1,0450	0,0245
Sing	0,0384	0,0619	0,0277	0,0349	1,3800	0,0277
Sport	0,0541	0,0857	0,0604	0,0488	1,2550	0,0488

Table 7. Comparison of matching algorithms

The decision-making stage is the last stage of the verification process. At this stage a decision is produced which method is best suited to use. To obtain such a decision, a comparison with the threshold value is required. To facilitate the decision-making process used the similarity measure method. The smaller the score then it can be assumed that the method is suitable. Table 8 shows the results of decision making using similarity measurement methods.

Task	Minkowski	Threshold	Score
Breath	0,0869	0,0869	0,4565
Color	0,0635	0,0635	0,4683
Face	0,0885	0,0885	0,4557
Finger	0,0268	0,0240	0,4880
Math	0,2100	0,2100	0,3950
Object	0,0369	0,0369	0,4815
Pass-thought	0,0245	0,0245	0,4877
Sing	0,0349	0,0277	0,4862
Sport	0,0488	0,0488	0,4756

Table 8. Decision-making process

5. Conclusions

Based on the measurement of similarity between features using distance measurement methods, Minkowski's distance method shows the smallest and near-zero scores. To facilitate the decision-making process used the method of measurement of similarity. The range of reference range used between 0 and 1. The smaller the score indicated by the distance between features shows the higher similarity level, and vice versa, the bigger the lower the similarity level.

From the cognitive task used as a stimulus, it is found that "Finger", "Pass-thought", "Sing", and "Object" tasks show the highest similarity scores with respective values of 0.4880, 0.4877, 0.4862, and 0.4815. The highest score is shown by two cognitive activities namely "Finger" and "Pass-thought"

with values of 0.4880 and 0.4877 with the lowest distance range 0.0268 and 0.0245. These results indicate that cognitive activity "Finger" and "Pass-thought" can provide more dominant signal characteristics.

Acknowledgments

This research is supported by The Indonesian Ministry of Research, Technology and Higher Education (RISTEK-DIKTI) research grant no. 118/SP2H/LT/DRPM/IV/2017.

6. References

- [1] A. Azhari, "Ekstraksi Ciri Gelombang Otak Menggunakan Alat Neurosky Mindset Berbasis Korelasi Silang.pdf," Universitas Gadjah Mada, Yogyakarta, 2015.
- [2] U. S. M. A. West Point Information and Educational Technology Division, "Biometrics Metrics Report." United States Military Academy West Point Information and Educational Technology Division, 2012.
- [3] D. Putra and K. Gede, "Sistem Verifikasi Biometrika Telapak Tangan dengan Metode Dimensi Fraktal dan Lacunarity," *Maj. Ilm. Teknol. Elektro*, vol. 8, no. 2, 2012.
- [4] D. Putra, Sistem Biometrika. Andi Offset, 2009.
- [5] A. Azhari and L. Hernandez, "Brainwaves feature classification by applying K-Means clustering using single-sensor EEG," *Int. J. Adv. Intell. Inform.*, vol. 2, no. 3, pp. 167–173, Nov. 2016.
- [6] J. Klonovs, C. K. Petersen, H. Olesen, and J. S. Poulsen, "Development of a Mobile EEG-Based Feature Extraction and Classification System for Biometric Authentication," Aalborg University Copenhagen, 2012.
- [7] I. Jayarathne, M. Cohen, and S. Amarakeerthi, "BrainID: Development of an EEG-based biometric authentication system," in *Information Technology, Electronics and Mobile Communication Conference (IEMCON), 2016 IEEE 7th Annual,* 2016, pp. 1–6.
- [8] P. Ackermann, C. Kohlschein, J. A. Bitsch, K. Wehrle, and S. Jeschke, "EEG-based automatic emotion recognition: Feature extraction, selection and classification methods," in *e-Health Networking, Applications and Services (Healthcom), 2016 IEEE 18th International Conference* on, 2016, pp. 1–6.
- [9] A. Patil, C. Deshmukh, and A. R. Panat, "Feature extraction of EEG for emotion recognition using Hjorth features and higher order crossings," in *Advances in Signal Processing (CASP)*, *Conference on*, 2016, pp. 429–434.
- [10]Y. Zhong and Z. Jianhua, "Recognition of Cognitive Task Load levels using single channel EEG and Stacked Denoising Autoencoder.pdf," in *Proceedings of the 35th Chinese Control Conference*, 2016, pp. 3907–3912.
- [11]C. F. H. Putra, "Analisis Citra Otak Pada Color-Task Dan Word-Task Dalam Stroop Task Dengan Menggunakan Electroencephalography (EEG)," Universitas Gadjah Mada, Yogyakarta, 2014.
- [12] A. A. Ghodake and S. D. Shelke, "Brain controlled home automation system," in *Intelligent Systems and Control (ISCO), 2016 10th International Conference on, 2016, pp. 1–4.*
- [13]B. Johnson, T. Maillart, and J. Chuang, "My thoughts are not your thoughts," 2014, pp. 1329– 1338.
- [14]R. F. Ahmad, A. S. Malik, N. Kamel, F. Reza, and A. H. A. Karim, "Simultaneous EEG-fMRI data acquisition during cognitive task," in *Intelligent and Advanced Systems (ICIAS)*, 2014 5th International Conference on, 2014, pp. 1–4.
- [15]M. Diykh, Y. Li, and P. Wen, "EEG Sleep Stages Classification Based on Time Domain Features and Structural Graph Similarity," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 11, pp. 1159–1168, Nov. 2016.
- [16]B. H. Tan, "Using a low-cost eeg sensor to detect mental states," Carnegie Mellon University, 2012.

- [17]E. Yulianto and A. Susanto, "Spesifikasi Ciri Sinyal EEG Untuk Perintah Pergerakan Motorik Berbasis Gelombang Singkat Khusus Berdasarkan Hasil Ekstraksi Ciri," Universitas Gadjah Mada, 2013.
- [18]M. Varela, "Raw EEG signal processing for BCI control based on voluntary eye blinks," in 2015 IEEE Thirty Fifth Central American and Panama Convention (CONCAPAN XXXV), 2015, pp. 1– 6.
- [19]A. Saha, A. Konar, P. Das, B. S. Bhattacharya, and A. K. Nagar, "Data-point and feature selection of motor imagery EEG signals for neural classification of cognitive tasks in car-driving," in 2015 International Joint Conference on Neural Networks (IJCNN), 2015, pp. 1–8.
- [20]N. K. Ratha, A. Senior, and R. M. Bolle, "Automated biometrics," in *International Conference on Advances in Pattern Recognition*, 2001, pp. 447–455.
- [21]A. Azhari, "Analisis Pengaruh Cognitive Task Berdasarkan Hasil Ekstraksi Ciri Gelombang Otak Menggunakan Jarak Euclidean," *SEMNASTEKNOMEDIA ONLINE*, vol. 5, no. 1, pp. 3–1, 2017.
- [22]A. Azhari, A. Susanto, and I. Soesanti, "Studi Perbandingan: Cognitive Task Berdasarkan Hasil Ekstraksi Ciri Gelombang Otak.pdf," presented at the Seminar Nasional Teknologi Informasi dan Multimedia, Yogyakarta, 2015, vol. 3.1, p. 7.
- [23] Trans Cranial Technologies ldt, "1020 System Positioning." Trans Cranial Technologies ldt, 2012.
- [24]A. Azhari, "Ekstraksi Ciri Gelombang Otak Menggunakan Alat Neurosky Mindset Berbasis Korelasi Silang.pdf," Universitas Gadjah Mada, Yogyakarta, 2015.
- [25]R. Zafar, A. S. Malik, H. U. Amin, N. Kamel, S. Dass, and R. F. Ahmad, "EEG spectral analysis during complex cognitive task at occipital," in *Biomedical Engineering and Sciences (IECBES)*, 2014 IEEE Conference on, 2014, pp. 907–910.