Human Computer Intelligent Interaction Based on sEMG Signals for Upper Limb Movements

[1]Dr. Kapil Joshi, [2]Dr Ritesh Rastogi, [3]Dr. Gunjan Chhabra, [4] Sheeba Praveen, [5]Rajesh Singh, [6]Rohit Kanauzia, [7]Michael G. Albino
[1]Department of CSE, UIT, Uttaranchal University, Dehtadun, India
[2](NIET) Noida institute of engineering and technology, Greater Noida, India
[3]Department of Systemics, school of computer science, UPES, Dehradun, India
[4]Computer Science Engineering, Integral University, Lucknow, India
[5]UIT, Uttaranchal University, Dehradun, India
[6]Department of CSE, College of Engineering Roorkee, India
[7]College of Communication and Information Technology President Ramon Magsaysay State University, Philippines

Abstract.

The role of human computer interaction in our lives has grown manifold in recent times. There is a requirement for more efficient, intelligent and concise interaction between humans and computers. It is significant to optimize this interaction by using efficient methods of calculation. For eliminating the data of interference for biometric recognition, and the simplification of the data processing, whilst improving efficiency of working of usual equipments for sEMG signals, the gesture recognition process for biometric scanning uses an approach based on the theory of variance. The action signals in all five groups become redundant and are visualized and divided into sixteen levels. The result comparison of recognizing the motion of thumb after removal of various channels which are redundant, the combination of optimal channels is acquired. Lastly, two types of classifiers apt for fields of sEMG signals are chosen and the outcomes of classification are weighed against each other, out of which the most efficient recognition pattern for thumb motion is concluded.

Keywords. Computer Intelligent System, sEMG signals, Human Intelligent.

1. Introduction

The process of simplification of the interaction between humans and computers is a hotspot in research for intelligent control Since human gestures are diverse, the human computer interaction development technology on the basis of recognizing gestures becomes increasingly significant [1,2]. sEMG (Surface Electromyography) is developed steadily in the human computer interaction wave. To perceive human motion, the reflection is on extension and flexion functions of the joints of hand and the information which is dynamic is reflected too, like the intensity and position of the limbs to complete certain actions. For thumb motion recognition, the issue caused by the electrode redundancy through sEMG is solved with the use of statistical Variance

Theory. This paper innovates the usage of statistical theory for eliminating the interfering signals formed by the channels which are redundant while acquiring certain actions specifically by universal sEMG signal usage through the equipment for their acquisition. Taking the research object of sEMG acquisition equipment with 16 channels, the electrodes that are redundant commonly are obtained with identification of the fine motion of the thumb for nine targets [3,4,5]. This research reduces the hardware cost and gives a reference to optimize the distribution of electrodes. It reduces the data processing overheads and saves time.

2. RELATED RESEARCH

Currently the researches in the field of recognition of human gestures focuses majorly on recognizing and classifying of gestures on large scale [6]. In everyday life, hand movements that are subtle with subtle arm, wrist and finger motions [7,8]. The thumb functions more than rest of the fingers do and in daily chores, it has the most functions. It is important to grasp at things and affects the gestures, position and motion of the hand on the whole. For rehabilitation sciences, the thumb movements can symbolize the complete hand posture and the hand movements to a limit and the thumb movements need to be studied deeply to understand the characteristics of motions for the control of the whole hand [9,10]. For human – computer interaction, a number of movements in a subtle manner of the thumb can facilitate the interactions of humans with computer [11,12,13,14]. Surface sEMG based gesture recognition is used for mainly collecting electrical signals which are generated on skin's surface by the equipment used for EMG acquiring. These are then classified and the data is recognized after extracting features. Recently, the myoelectric signals have been studied by many scholars in the human computer interaction field [15]. The influence of classification and feature algorithm was studied by Xun Chen et. al for accuracy of recognition. This experiment included the use of four channel acquisition equipment for sEMG and the signals for forearm sEMG were used for collecting ten gestures of the Chinese language. With the combination of the traditionally used features with the newer algorithm for classification, the accuracy of recognition of the motions of the hand has been 95% more improved [16]. sEMG signals were used by Jongin Kim et. al. for identifying the space scaling between user's thumb and the index finger on the screen of a device [17]. Four features were extracted by Chengcheng Li et. al out of the 9 gestures and they used an SVM classifier for recognizing gestures to a 98% accuracy [18].

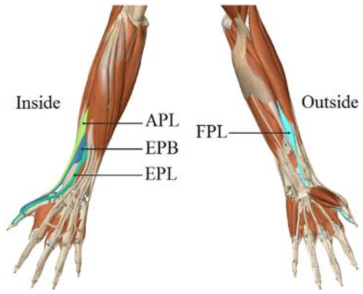

Figure 2.1. Muscle group on Outside [8]

A tactile sensor was used by G.F. Li et. al for the process of recognition of EMG gestures [19]. A device was designed by Nor Anija Jalaludin et. al. for detection of the sEMG strength and the sEMG model was established to decipher the dependability of the force of thumb and its angle [20]. The hand tools were optimized by Essam Odah et. al. for testing of the strain with various positions of sEMG signals comparatively [21, 22]. The thumb is connected to the muscle groups which can be divided into the external and internal groups of muscles [23, 24]. The hand includes most of the inner adnexal group of muscles and the outer one is distributed in the arm mainly. The inside group of muscles constitutes of the abductor pollicis bevis, abductor pollicis brevis, opponent pollicis and first dorsal interossus. The outside muscle group includes the extensor pollicis brevis, flexor pollicis longus and the abductor pollicis longus, as seen from Figure 2.1.

3. METHODS AND MATERIALS

3.1. Acquisition Equipment Selection

Equipment to acquire sEMG function mainly for storing and filtering the electrical signals which are generated by the surface of the skin. As EMG signals are weak and can be interfered with easily along with the bioelectric signals, the signal quality relates closely with the acquisition equipment generally [25,26]. The equipment selected in this research includes an 18 channel technology with a technique for spatio temporal resolution sampling, which is compatible with both wet and dry electrodes and communication technology based on Bluetooth wireless signals, used to analyze gait, muscles' fatigue, gesture recognition, rehabilitating treatment, etc. These equipments are very easily available in the market for collection of the sEMG signals of the upper limbs. Most research tasks are met on the basis on EMG signals. From figure 2 one can see the equipment used for the research. The system for signal acquisition used in this paper has 17 dry electrodes used in a fabric form, which makes it flexible and 15 sEMG bipolar channels are thus formed, thus reducing the artifact use, one of these electrodes is used for grounding and the other electrode is used for reference. Rest of the 15 electrodes are distributed evenly in the sleeve.

Figure 3.2. Acquisition Equipment [16]

3.2. Process Design for Experiment

For fingers, there is a well established international standard which judges the flexibility and the standard's core is if the thumb is able to touch easily rest of the 4 fingers. Hence, five gestures which are dynamic, are dynamic, are selected on the basis of the norms [32,33]. These gestures are UP (thumb moves upward – relax), DOWN (Thumb down – relax), LEFT, RIGHT and PRESS. Figure 3.2 shows the actions in all the five gestures. Ten subjects were used, with 3 women and 7 men between ages of 25 to 35 , who were healthy, with no motor nerve issue history and the activities were of higher intensity in the time preceding the research. For acquiring data, the test needs the subjects to be in a sitting position, with elbows over the table and naturally suspended forearms. Every subject measure six data sets, with six gestures types, each repeated 12 times. This data was collected over a week, forming the dataset.

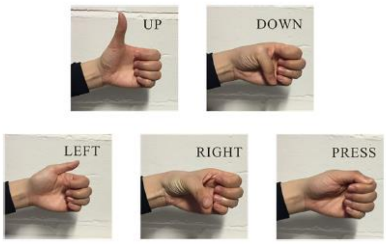

Figure 3.2. Types of Gestures [9]

4. WAVE FILTERING

This operation filters out the regularity in a specifically selected band of the gesture and it is significant to gauge and suppress the obstruction. The discrete output signal is converted by the digital filter into another one, based on the real time need, as shown in figure 4.1.

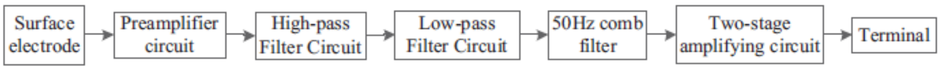

Figure 4.1 Flow of Signal Processing

Since the sEMG indicator is weak, it is imperative to strengthen the electric signals assembled by the first electrode all the way through the circuit for pre-amplification. The next step includes using a high pass filter and using of low pass filter for the noise for wake in 20 Hz and above 500 ambient noise. The filtered signal is finally amplified doubly for fitting in the equipment used for acquisition.

4.1. Detecting Active Segment

All the gestures in the experiment are dynamic and the time used for relaxing while the data is being collected is not very precise. So it is important to get rid of the signals which are redundant with the relaxation time, and the signals of the gestures that are intercepted should also consist of the complete process of movement, and the job of the detection of the segment of activity is determining the beginning and conclusion of the gesture [37, 38, 39]. The method used for moving the average has a defined width of the window for sliding of the signal and comparison of the sequence of immediate energy with a threshold value found in real time for determining the starting and ending points of the signal for gestures [40]. The sEMG signal value alters from +ve to –ve in considerably shorter span and the random fluctuations are very large, so that the method for moving average is suitable for elimination of the fluctuation of interference and getting the signals's overall trend.

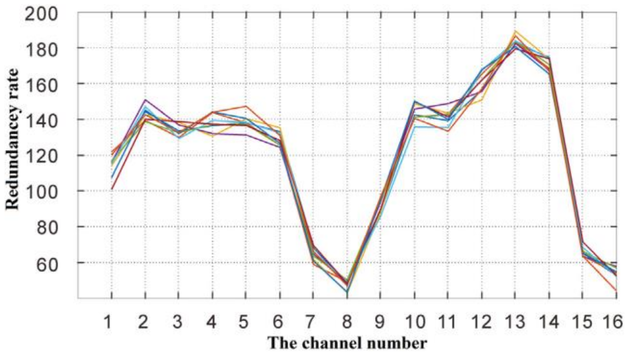

Figure 4.2. Weighted Redundancy of Channels

4.2. Extracting Features

The best features are selected for the methods using time and domain, which are the feature with the absolute mean value, zero crossing feature, feature with the change in slope sign, autoregressive mode, slope sign change feature and the root mean square feature [42,43,44]. Through the validation of clustering, one finds that the amalgamation of RMS, AR and SSC, gives the best effect for classification.

5. RESULTS AND DISCUSSIONS

For achieving better results, there is the need for a classifier to be selected, which has certain advantageous [45] features. Presently, the classifiers used for mainstream classification of limb motions, include LDA or Linear Discriminant Analysis, ANN or Artificial Neural Network, GMM [46-48] or Gaussian Mixture Model, SVM or Support Vector Machine, GRNN or Generalized Regression Neural Network, HMM or Hidden

Markov Model, etc. Out of all these, SVM gives a much better performance and the meticulous mathematical theory it has and the performance of good classification renders it to be used widely for electromyography [49]. Hence the preferred choice for this experiment is SVM. GRNN has a strong ability for both [50] approximation and classification, making the learning rate better than RBF Neural Network (Radial Phase Foundation) and Neural Network with a Back Propagation [51-55] Algorithm (BP), and performance is better. The noise data classification problem uses a GRNN as the second choice classifier.

6. CONCLUSION

To begin with, the dynamic gestures are defined; the raw data collected and subsequently is filtered. Futher, the detection of the active segment is performed, and the feature selection is done. This was followed by the calculation of, the redundancy for every channel's electrode, using dispersion theory. Using a simple coding method, three kinds of overlapping combinations for the electrodes generated. The reference classifiers were taken as the SVMs and 12, 13, and 14 channels were eliminated and the best channels were removed. Finally, the comparison between the effects of classification of GRNN and SVM were done in 16 and 13 channels, proving that the overlapping electrode which was removed, is the electrode which overlaps commonly.

7. REFERENCES

[1] G.F. Li, H. Wu, G.Z. Jiang, S. Xu, H.H. Liu, Dynamic gesture recognition in the internet of things, IEEE Access 7 (2019) 23713–23724.

[2] M. Balouchestani, S. Krishnan, Robust compressive sensing algorithm for wireless surface electromyography applications, Biomed. Sign. Process. Control 20 (2015) 100–106.

[3] Z. Jiang, Y. Jiang, Y. Wang, H. Zhang, H.J.C.G.D. Tian, A hybrid approach of rough set and case-based reasoning to remanufacturing process planning, J. Intell. Manuf. 30 (1) (2019) 19–32.

[4] G.R. Naik, S.E. Suviseshamuthu, M. Gobbo, Principal component analysis applied to surface electromyography: a comprehensive review, IEEE Access 4 (2016) 4025–4037.

[5] H. Wang, Z.G. Jiang, H. Zhang, Y. Wang, Y.H. Yang, Y. Li, An integrated MCDM approach considering demands-matching for reverse logistics, J. Clean. Prod. 208 (2019) 199–210.

[6] D.S. Chen, G.F. Li, Y. Sun, J.Y. Kong, G.Z. Jiang, H. Tang, Z. J. Ju, H. Yu, H.H. Liu, An interactive image segmentation method in hand gesture recognition, Sensors 17 (2) (2017) 253.

[7] S. Mustafa, I. Elghandour, M.A. Ismail, A machine learning approach for predicting execution time of spark jobs, Alexandr. Eng. J. 57 (1) (2018) 3767–3778.

[8] M. Tavakoli, C. Benussi, J.L. Lourenco, Single channel surface EMG control of advanced prosthetic hands: a simple, low cost and efficient approach, Exp. Syst. Applic. 79 (2017) 322–332.

[9] J.B. Hu, Y. Sun, G.F. Li, G.Z. Jiang, B. Tao, Probability analysis for grasp planning facing the field of medical robotics, Measurement 141 (2019) 227–234.

[10] G.F. Li, D. Jiang, Y.L. Zhou, G.Z. Jiang, J.Y. Kong, Gunasekaran Manogaran, Human lesion detection method based on image information and brain signal, IEEE Access 7 (2019) 11533–11542.

[11] A.R. Siddiqi, S.N. Sidek, A. Khorshidtalab, Signal Processing of EMG Signal for Continuous Thumb-Angle Estimation, IECON, 2015, pp. 374–379.

[12] J.X. Qi, G.Z. Jiang, G.F. Li, Y. Sun, B. Tao, Intelligent human computer interaction based on surface EMG gesture recognition, IEEE Access 7 (2019) 61378–61387.

[13] Y.F. Fang, D.L. Zhou, K.R. Li, H.H. Liu, Interface prostheses with classifier-feedback-based user training, IEEE Trans. Biomed. Eng. 64 (11) (2017) 2575–2583.

[14] R. Menon, C.G. Di, H. Lakany, L. Petropoulakis, B. Conway, J. Soraghan, Study on interaction between temporal and spatial information in classification of EMG signals in myoelectric prostheses 1–1, IEEE Trans. Neural Syst. Rehabil. Eng. (2017), https://doi.org/10.1109/TNSRE.2017.2687761.

[15] Y. Sun, C.Q. Li, G.F. Li, G.Z. Jiang, D. Jiang, H.H. Liu, Z.G. Zheng, W.N. Shu, Gesture recognition based on kinect and sEMG signal fusion, Mobile Netw. Applic. 23 (4) (2018) 797–805.

[16] X. Chen, Z.J. Wang, Pattern recognition of number gestures based on a wireless surface EMG system, Biomed. Signal Process. Control (2013) 184–192.

[17] J. Kim, D. Cho, K. Lee, B. Lee, A real-time pinch-to-zoom motion detection by means of a surface EMG-based human computer interface, Sensors 15 (1) (2014) 394–407.

[18] C.C. Li, G.F. Li, G.Z. Jiang, D.S. Chen, H.H. Liu, Surface EMG data aggregation processing for intelligent prosthetic action recognition, Neural Comput. Appl. (2018), https://doi.org/10.1007/s00521-018-3909-z.

[19] G.F. Li, L.L. Zhang, Y. Sun, J.Y. Kong, Towards the sEMG hand: internet of things sensors and haptic feedback application, Multim. Tools Applic. 78 (21) (2019) 29765–29782.

[20] N.A. Aranceta, B.A. Conway, Differentiating variations in thumb position from recordings of the surface electromyogram in adults performing static grips, a proof of concept study, Front. Bioeng. Biotechnol. 7 (2019), https://doi.org/10.3389/fbioe.2019.00123.

[21] E. Odah, I. Abu-Qasmieh, N. Al Khateeb, E. Al Matalbeh, S. Quraan, M. Mohammad, Gender considerations in optimizing usability design of hand-tool by testing hand stress using SEMG signal analysis, Alexandr. Eng. J. 57 (4) (2018) 2897–2901.

[22] K. Usha, M. Ezhilarasan, Fusion of geometric and texture features for finger knuckle surface recognition, AEJ – Alexandr. Eng. J. 55 (1) (2016) 683–697.

[23] S. Kim, J. Kim, M. Kim, S. Kim, J. Park, Grasping force estimation by sEMG signals and arm posture: tensor decomposition approach, J. Bion. Eng. 16 (3) (2019) 455–467.

[24] R.R. Muhammad, N.S. Shahrul, F.T. Siti, Portable thumb training system for EMG signal measurement and analysis, in: International Conference on Computer and Communication Engineering, 2016, https://doi.org/10.1109/ICCCE.2016.44.

[25] D. Jiang, G.F. Li, Y. Sun, J.Y. Kong, B. Tao, D. Chen, Grip strength forecast and rehabilitative guidance based on adaptive neural fuzzy inference system using sEMG, Pers. Ubiquit. Comput. (2019), https://doi.org/10.1007/s00779-019-01268-3.

[26] Z.O. Khokhar, Pattern Recognition of Surface Electromyography Signals for Real-time Control of Wrist Exoskeletons, vol. 9, 2010, pp. 24–41
[27] D. Jiang, Z.J. Zheng, G.F. Li, Y. Sun, J.Y. Kong, G.Z. Jiang, H. G. Xiong, B. Tao, S. Xu, H.H. Liu, Z.J. Ju, Gesture recognition based on binocular vision, Clust. Comput. 22 (Supplement 6) (2019) 13261–13271.
[28] M.C. Yu, G.F. Li, D. Jiang, G.Z. Jiang, F. Zeng, H.Y. Zhao, D. S. Chen, Application of Pso-Rbf neural network in gesture recognition of continuous surface EMG signals, J. Intell. Fuzzy Syst. (2019), https://doi.org/10.3233/jifs-179535.
[29] Y.W. Cheng, G.F. Li, J.H. Li, Y. Sun, G.Z. Jiang, F. Zeng, H. Y. Zhao, D.S. Chen, Visualization of activated muscle area based on sEMG, J. Intell. Fuzzy Syst. (2019), https://doi.org/ 10.3233/jifs-179549.
[30] Y. He, G.F. Li, Y.J. Liao, Y. Sun, J.Y. Kong, G.Z. Jiang, D. Jiang, H.H. Liu, Gesture recognition based on an improved local sparse representation classification algorithm, Clust. Comput. 22 (Supplement 5) (2019) 10935–10946.
[31] E.N. Kamavuako, D. Farina, K. Yoshida, W. Jensen, Estimation of grasping force from features of intramuscular EMG signals with mirrored bilateral training, Ann. Biomed. Eng. 40 (3) (2012) 648–656.
[32] X. Zhai, B. Jelfs, R.H. Chan, Short latency hand movement classification based on surface EMG spectrogram with PCA, in: Conf Proc IEEE Eng Med Biol Soc, 2016, pp. 327–330.
[33] M. Kim, K. Kim, W.K. Chung, Simple and fast compensation of sEMG interface rotation for robust hand motion recognition 1–1, IEEE Trans. Neural Syst. Rehabil. Eng. (2018).
[34] Kasiprasad Mannepalli, Panyam Narahari Sastry, Maloji Suman, A novel adaptive fractional deep belief networks for speaker emotion recognition, Alexandr. Eng. J. 56 (4) (2017) 485–497. https://linkinghub.elsevier.com/retrieve/pii/S1110016816302484,https://doi.org/10.1016/j.aej.2016.09.002.
[35] H. Kalani, S. Moghimi, A. Akbarzadeh, SEMG-based prediction of masticatory kinematics in rhythmic clenching movements, Biomed. Sign. Process. Control 20 (2015) 24–34.
[36] T. Al, A. Ahmad, J. Al, Adel, Optimal Feature Set for Finger Movement Classification Based on SEMG, IEEE Engineering in Medicine and Biology Society, 2018, pp. 5228–5231.
[37] M.C. Yu, G.F. Li, D. Jiang, G.Z. Jiang, B. Tao, D.S. Chen, Hand medical monitoring system based on machine learning and optimal EMG feature set, Pers. Ubiquit. Comput. (2019),
https://doi.org/10.1007/s00779-019-01285-2.
[38] M.R. Al-Mulla, F. Sepulveda, Super wavelet for sEMG signal extraction during dynamic fatiguing contractions, J. Med. Syst. 39 (1) (2015) 167.
[39] T.F. Yang, J.W. Wang, Z.G. Hu, Variation of neck electromyography and mechanical characteristics during the process of cervical traction, J. Med. Biomech. 31 (5) (2016) 421–425.
[40] K. Veer, T. Sharma, A novel feature extraction for robust EMG pattern recognition, J. Med. Eng. Technol. 40 (4) (2016) 6.
[41] S. Guo, M. Pang, B. Gao, Comparison of sEMG-based feature extraction and motion classification methods for upper-limb movement, Sensors 15 (4) (2015) 9022–9038.

[42] J.X. Qi, G.Z. Jiang, G.F. Li, Y. Sun, B. Tao, Surface EMG hand gesture recognition system based on PCA and GRNN, Neural Comput. Appl. (2019), https://doi.org/10.1007/s00521-019-04142-8.

[43] O.A. Moura Karina, R.S. Ruschel, A. Balbinot, Fault-Tolerant Sensor Detection of sEMG Signals: Quality Analysis Using a Two-Class Support Vector Machine, IEEE Engineering in Medicine and Biology Society, 2018, pp. 5644–5647.

[44] P. Karthick, G. Venugopal, S. Ramakrishnan, Analysis of Muscle Fatigue Progression using Cyclostationary Property of Surface Electromyography Signals, Plenum Press, 2016,https://doi.org/10.1007/s10916-015-0394-0.

[45] G.F. Li, J.H. Li, Z.J. Ju, Y. Sun, J.Y. Kong, A novel featureextraction method for machine learning based on surfaceelectromyography from healthy brain, Neural Comput. Appl.31 (12) (2019) 9013–9022.

[46] G.F. Li, H. Tang, Y. Sun, J.Y. Kong, G.Z. Jiang, D. Jiang, B.Tao, S. Xu, H.H. Liu, Hand gesture recognition based on convolution neural network, Clust. Comput. 22 (Supplement 2) (2019) 2719–2729.

[47] M. Nisser, S. Derlien, U.C. Smolenski, N. Best, Measurement of muscular load with sEMG in using different computer input devices - a pilot study, Physikalische Medizin Rehabilitations medizin Kurortmedizin 28 (2018) 231–234.

[48] D. Kaneishi, R.P. Matthew, M. Tomizuka, A sEMG Classification Framework with Less Training Data, IEEE Engineering in Medicine and Biology Society, 2018, pp. 1680–1684.

[49] B. Zhou, X.L. Ji, R. Zhang, Design of surface EMG acquisition instrument based on embedded technology, Mod. Electr. Tech.33 (6) (2010) 55–57.

[50] B.W. Luo, Y. Sun, G.F. Li, D.S. Chen, Z.J. Ju, Decomposition algorithm for depth image of human health posture based on brain health, Neural Comput. Appl. (2019), https://doi.org/10.1007/s00521-019-04141

[51] Bagwari, S., Gehlot, A., Singh, R., Priyadarshi, N., & Khan, B. (2022). Low-Cost Sensor-Based and LoRaWAN Opportunities for Landslide Monitoring Systems on IoT Platform: A Review. IEEE Access, 10, 7107–7127. https://doi.org/10.1109/ACCESS.2021.3137841

[52] Malik, P, Gehlot, A., Singh, R., Gupta, L. R., & Thakur, A. K. (2022). A Review on ANN Based Model for Solar Radiation and Wind Speed Prediction with Real-Time Data. Archives of Computational Methods in Engineering. https://doi.org/10.1007/s11831-021-09687-3

[53] Singh, R., Gehlot, A., Rashid, M., Saxena, R., Akram, S. V, Alshamrani, S. S., & Alghamdi, A. S. (2021). Cloud server and internet of things assisted system for stress monitoring. Electronics (Switzerland), 10(24). https://doi.org/10.3390/electronics10243133

[54] Karunanidy, D., Ramalingam, S., Dumka, A., Singh, R., Rashid, M., Gehlot, A., ... & AlGhamdi, A. S. (2022). JMA: Nature-Inspired Java Macaque Algorithm for Optimization Problem. Mathematics, 10(5), 688.

[55] Sharma, V. K., Singh, R., Gehlot, A., Buddhi, D., Braccio, S., Priyadarshi, N., & Khan, B. (2022). Imperative Role of Photovoltaic and Concentrating Solar Power Technologies towards Renewable Energy Generation. International Journal of Photoenergy, 2022.

Biographies

Dr. Kapil Joshi received the Ph.D. degree in computer science & engineering from Uttaranchal University in 2021, the master's degree in Information Technology from Graphic Era University in 2014. He has published various patents, research papers in reputed journals (UGC/Scopus) as well as published two books in international publication. He was also a student member of IEEE UP section in session 2019-20 and editorial member, guest editor in various reputed national/international journals. He has been awarded with “Best Young Researcher" Award in Global Education and Corporate Leadership (GECL-21) received by Life Way Tech India Pvt. Ltd. in 2021, He also appointed as an Asia Coordinator in “International Association for the promotion of Asia-Africa Research” (IAPAAR) from 2020.