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Distributed Multimodal Brain Monitoring Using Body-Area Sensor Arrays

Metahun Lemeon[1*], Jinfe Regash[2], Tasil Leyene[3]
[1-3]Electrical and Computer Engineering Addis Ababa University Addis Ababa, Ethiopia

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Author's Email:
meta.lemeon@aait.edu.et,
jin.regash@aait.edu.et,
ley.tas@aait.edu.et

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Abstract
The wearable sensing technologies of continuous brain monitoring have become a central facilitator of healthcare, assistive systems, and humancomputer interaction. But the majority of solutions available to date use centralised data acquisition and processing designs, which have been plagued by scalability, cost issues, go directly through the communication line and cannot be trusted in long-term deployments. It is necessary to overcome these shortcomings; to this end, the present paper introduces a distributed Internet of Things (IoT)-based body area sensor network (BASN) architecture in multimodal brain monitoring. The presented system incorporates the electroencephalography (EEG), inertial, and auxiliary physiological sensors in a wireless body-area network to supply it with the possibility of real-time operation, energy efficiency, and scalability. Its architecture takes the form of hierarchical and distributed architecture that includes the low powered body worn sensor nodes, edge-enabled body coordinator, and cloud / fog based services. Preprocessing and feature extraction are done locally at sensor and coordinator levels to minimise communication overhead as well as enhance responsiveness. The energy-conscious communication plan is used to optimise the data transfer in order to ensure the consistent synchronisation of multiple sensor streams of various modalities. The system is tested by way of simulation in different networking conditions and sensor densities. Performance data prove that the distributed architecture proposed allows to reduce end-to-end latency by a factor, end node energy used by a factor, and the percentage of packet delivery by a factor than the same architecture would provide in a traditional centralised scheme based on monitoring. These results prove the usefulness of distributed sensing and edge-assistance data management in body area networks. The suggested framework offers a scalable and implementable platform of next-generation IoT-bases brain monitoring systems and other wearable cyber-physical health smolutions.

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Introduction
The use of the current wearable sensing technologies and low-power wireless communication has made it possible to record physiological and neurological activities outside controlled clinical settings. One of them, electroencephalography (EEG), which is often complemented by other complementary physiological and motion-related evidence, has gained prominence in various applications specifically neurorehabilitation, mental health treatment, cognitive load analysis, assistive technology, and human-computer interfaces.[1, 2] The increasing need and necessity in long term, real-time and unobtrusive monitoring of the brain has increased the pace in the development of wearable

and body mounted sensor platforms. In spite of this development, the vast majority of the existing brain monitoring systems are based on centralised data acquisition and processing design, in which raw sensor signals are delivered to a central processing unit or remote server in a continuous fashion. The major weaknesses of such centralised designs are that they are not very scalable as the sensors begin growing, they consume a lot of energy since they keep transmitting data wirelessly, performance is slow because of communication delay, and they are also susceptible to single points of failure.[3, 4] These issues severely limit their applications in real-life deployment in continuous and large-scale applications. The promising alternative is represented by the Body Area Sensor Networks (BASNs), a special form of wireless sensor networks that provide an opportunity to accomplish distributed sensing and local data processing across the body-worn sensors. Combined with Internet of Things (IoT) paradigms, BASNs can facilitate edge intelligence, adjustable communication, and uninterrupted communication with cloud-based platforms of analytics.[5, 6] Non-trivial issues, however, arise in designing a distributed BASN to monitor a multimodal brain in terms of time synchronisation among heterogeneous sensors, energy saving wireless communication, faultless data aggregation and scalability of system specifications. Current literature is mainly concerned with the sensor design or signal analysis but the system-level distributed networking architecture and energy conscious communication scheme is not well studied, especially when addressing multimodal brain monitoring case.[7, 8]

In order to fill these gaps, this paper presents a distributed IoT-based body area sensor network architecture that is used to monitor multimodal brain. The suggested framework incorporates the EEG, inertial and physiological sensors in a hierarchical and energy conscious wireless body-area network. It uses edge-level preprocessing to minimise the communication overhead and distributed data management to ensure real-time performance is provided. The performance of the suggested architecture is considered using performance analysis based on simulation where latency, energy usage and consistency in delivery of packets are testing factors.

The rest of the paper is structured in the following way. Section 2 presents the review of related literature on wearable brain monitoring systems and BASN-based healthcare systems. Section 3 shows the proposed system architecture. Section 4 outlines the strategy of communication and data management. Section 5 is on performance evaluation and results. Last, Section 6 wraps up the paper and gives detailed future research directions.

Related Work

The wireless brain monitoring systems are a well-researched field in terms of wearable electroencephalography (EEG) monitors and health-related Internet of Things (IoT) systems. Early studies mainly involved single-modality EEG recording devices, and in this case, raw signals of the brain were passed on to a central point of processing that would be analysed.[11, 12] Although these architectures proved to be viable in controlled or short term monitoring applications, they are inherently restricted by excessive energy consumption, high wireless bandwidth utilisation and bad scalability with increase in channels of sensing.[10] As the idea of IoT-based healthcare systems was introduced, a number of studies have suggested the use of wearable monitoring platforms that also combine body area sensor networks (BASNs) and cloud-based analytics.[4, 5] These systems provide support through remote access and long-term data storage as well as signal processing. More recent models have taken the multimodal sensing method, that is, using EEG with inertial measurement units (IMUs), electrocardiography (ECG) or electromyography (EMG) to enhance the robustness, motion awareness, and contextual interpretation of brain activity.[6, 7] Even though multimodal sensing improves the accuracy of the monitoring, much of these solutions still heavily depend on the centralization of data aggregation and processing, and this leads to higher end-to-end delays and communication overhead. In order to address these shortcomings, new paradigms such as distributed sensor network architecture and edge computing have been proposed in wearable and healthcare Internet of Things.[8, 9] These methods enable even better real-time responsiveness and reduce bandwidth demand because local preprocessing/feature extracting or data compression algorithms are performed at sensor nodes or edge gateways, removing the need to transfer these high-rate data (or even the occasionally very low-rate data). Nevertheless, the current edge-assisted systems tend to be tailored towards physiological high in general and fail to explicitly cover the special networking requirements of multimodal brain monitoring: stringent synchronisation constraints, heterogeneous data rates, and energy-restricted body-worn devices.

In general, although wearable EEG systems, multimodal sensing, and IoT-based healthcare platforms have made a major advancement, fully distributed body area sensor network architectures with multimodal brain monitoring applications have not been adequately investigated. Specifically, system-level designs that collaboratively capture energy-aware communication, distributed data management and performance evaluation, based on wireless networking viewpoint are unavailable. This shortcoming is an incentive to develop the distributed IoT-based BASN architecture, which is suggested in the given work.

System Architecture

Overview

The given research proposal uses three-tier distributed system architecture to provide scalable, multimodal brain monitoring in terms of real-time and energy-efficient aspects. The architecture is made up of body sensor nodes, body coordinator which acts as edge node, and cloud or fog based IoT services, as shown in Fig. 1. This hierarchical architecture allocates sensing, processing and communication functions to various levels hence eliminating the dependency on a central processing area and avoidance of latency and power limitations. The study was carried out by developing the system as a cyber-physical internet of things network whereby raw physiological data are partly processed near an actual sensor, aggregated by an intermediate edge node, and analytic functions are

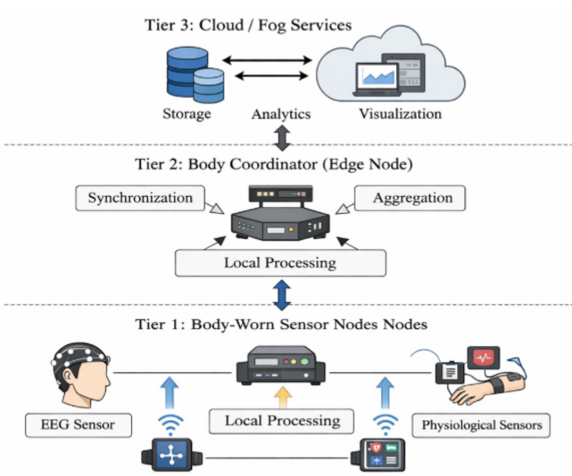

Fig. 1: Distributed IoT-Based Body Area Sensor Network Architecture for Multimodal Brain Monitoring

processed by the higher-level model in the cloud node. This is achieved by the separation of responsibilities which enables the dynamic adherence of the system to heterogeneous sensor data rate and input under varying network conditions whilst keeping continuous monitoring performance.

IoT-based body area sensor network architecture Three-level architecture The architecture of multimodal body sensors, body coordinator, which provides synchronisation and aggregation, and analytics/visualisation using cloud/fog devices.

Sensor Nodes

The sensor layer has several low-power wearable nodes that are distributed over the body. Every node has a single or a combination of sensing modalities, such as neural activity sensing via electroencephalography (EEG) electrodes, motion awareness and sensing via inertial measurement units (IMUs), and additional physiological sensors (such as heart rate sensors or skin conductance sensors), as well. These nodes use limited power capabilities and they are aimed at the reduction of wireless packet transmission overhead.
Each sensor node has analogue signals which are conditioned and digitised first and subsequently lightweight local pre-processing. Let x_i (t) represent the raw signal acquired by the i-th sensor modality at time t. Local preprocessing is applied as

$$\tilde{x}_i(t) = f_i\big(x_i(t)\big) \tag{1}$$

where f_i (·) denotes modality-specific operations such as band-pass filtering for EEG signals or statistical feature extraction for inertial data. By transmitting $x\sim_i$ (t) instead of raw signals, the system significantly reduces communication load and energy consumption. There is also use of event driven reporting capability that as such, the transmission of data is only done when significant signals changes are realised.

Body Coordinator (Edge Node)

The body coordinator serves as a body area sensor network control and edge processor. It takes care of network co-ordination, time co-ordination, data aggregation, and in-between processing. The coordinator obtains processed data packets via several sensor nodes and synchronises them in time in order to facilitate multimodal data fusion.

Let $x\sim_i^k$ denote the preprocessed data packet received from sensor node i during the k-th transmission interval. The aggregated multimodal data set at the coordinator is represented as

$$X^k = \{\tilde{x}_1^k, \tilde{x}_2^k, \dots, \tilde{x}_N^k\} \tag{2}$$

N number of active sensor nodes. The coordinator also carries out other processing including feature-level fusion, data compression, or anomaly screening until higher levels are received with the relevant information. The edge-level processing lowers the end-to-end latency and bottlenecks unwarranted data transfer to the cloud.

Short distance, low-power wireless protocols like the Bluetooth Low Energy (BLE) or the IEEE 802.15.6 have been adopted as sensor node to body coordinator wireless communication as these protocols will be suitable in the requirements of body-area networking applications.

Cloud and IoT Services

The architecture above is composed of cloud or fog-based IoT services offering a scalable computation and also long-term storage and advanced analytics. Data packets sent to the body coordinator are collected and sent to this layer through the standard IoT communication protocols. On the cloud, machine learning models and longitudinal analysis tools can be used to analyse trends, evaluate cognitive states or help in making decisions. The remote monitoring and visualisation performable with the cloud layer also allows clinicians or system administrators to view system outputs in real time. The system is capable of saving energy by transferring the tasks requiring much calculation to wearable devices whilst retaining the ability to analyse and compare information.

Communication and Data Management

Energy-Aware Communication Strategy

The research uses adaptive sampling and transmission control with energy reliant communication strategy to satisfy energy needs of wearable sensor nodes as there is limited energy resource at the sensor node itself. The sensor nodes automatically change the rate at which they sample based on the amount of residual energy they have. Let E_i represent the remaining energy of sensor node i. The adaptive sampling rate r_i is defined as

$$r_i = r_{max} \cdot \frac{E_i}{E_{max}} \tag{3}$$

where r_{max} is the maximum allowable sampling rate and E_{max} is the initial energy capacity. This process provides long network lifetime and a fidelity of the data to be used in brain monitoring.

Data Aggregation and Throughput Optimization

In order to minimise network congestion and enhance throughput, data aggregation is done at body coordinator as depicted in Fig. 2. The coordinator does not pass one packet at a time but instead takes the information of several sensor nodes and packages them into aggregated packets. If P_i denotes the packet generated by sensor node i, the aggregated packet is expressed as

$$P_{agg} = \bigcup_{i=1}^{N} P_i \tag{4}$$

Such aggregation strategy minimises protocol overhead, optimises bandwidth use and maximises network efficiency, and is especially effective in high density sensor deployments.

Synchronization, Reliability, and Security

Multimodal brain monitoring requires the accurate time organisation. The system uses alignment by regular synchronization messages and timing based alignments that guarantee temporal consistency of heterogeneous streams of data. The system as shown in Fig. 2 uses

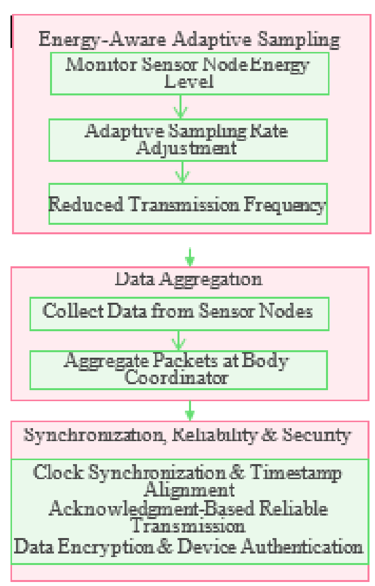

Fig. 2: Energy-Aware Communication and Data Management Workflow in the Proposed BASN

periodical synchronisation messages, timestamps-based alignment systems, to ensure that the data is consistently correlated. The reliability is increased in terms of the recognition-based retransmission mechanisms and the adaptive transmission power control to address the loss of packets. In order to preserve physiological and neurological information that may be sensitive, lightweight security mechanism are added to the communication layer. Data communication is performed with encryption, and device authentication algorithms are applied to avoid unauthorised access and contain moderate computer computation needed by the wearable devices with limited financial resources.

The block flowchart of the proposed body area sensor network is a flow chart that shows adaptive sampling, data aggregation, data synchronisation, and a secure communication.

Performance Evaluation

Simulation Setup

Simulation environment A discrete-event simulation environment was used to evaluate the performance of the proposed distributed body area sensor network (BASN) architecture based on realistic body-area communication scenarios. The simulated network has several wearing sensor nodes placed in parts of the body and wirelessly connecting to a body coordinator that is an edge node. The coordinator consolidates the sensor data and sends pertinent data to either the cloud services or the fog services to process it. All sensor nodes start with a limited amount of energy and the sensor nodes work in conditions of the real wireless channel with path loss and probability of packet error. The most important simulation parameters are sensor node energy capacity, packet size, adaptive sampling rates, transmission times, as well as node density. In order to estimate the performance of the proposed design, the performance of the proposed design is compared to a traditional centralised architecture when all sensor nodes send raw data directly to a central processing unit without edge-level preprocessing and aggregation. Several simulation scenarios with a different network condition were carried out to provide statistical consistency, and average values were provided to all performance measurements.

Performance Metrics

The evaluation of the performance is based on four important metrics that are popular in the field of wireless sensor network and IoT research:

End-to-end latency is a set of measures that determine the average time that packets of data will take to move between sensor nodes and the last processing layer, namely; transmission- aggregation and processing delay. Reduced time of latency is a sign of enhanced suitability to real-time monitoring.

Energy per node is the mean power that the sensor node uses to operate. This measure directly indicates the concept of the efficiency of the suggested energy-conscious communication plan.

Table 1. Simulation Parameters Used for Performance Evaluation

Parameter	Description	Value / Range
Network type	Body Area Sensor Network (BASN)	Distributed / Centralized
Number of sensor nodes (N)	Body-worn wearable sensor nodes	5, 10, 15, 20
Sensor modalities	EEG, IMU, physiological sensors	Multimodal
Initial energy per node (Emax)	Battery capacity of each sensor node	0.5 J
Adaptive sampling rate (ri)	Energy-aware sampling rate	10–250 Hz
Maximum sampling rate (rmax)	Upper bound of sampling frequency	250 Hz
Packet size	Data payload per transmission	64–256 bytes
Wireless protocol	Body-area communication standard	BLE / IEEE 802.15.6
Transmission range	Sensor-to-coordinator distance	1–3 m
Data aggregation point	Edge-level aggregation	Body coordinator
Channel model	Wireless body-area channel	Path loss + packet error
Simulation duration	Time per simulation run	1,000 s
Number of simulation runs	Repeated experiments for averaging	10 runs
Performance comparison	Baseline architecture	Centralized system

Packet delivery ratio (PDR) is given as a ratio between packets that have been correctly received to the amount of packets sent out. An increase in PDR means that there is enhanced reliability in communication.

Network scalability measures the system performance with respect to the number of sensor nodes, and measures whether the system exhibits stability in terms of latency, power consumption as well as packet delivery in a dense deployment.

Results and Discussion

Results of the simulation prove that the proposed distributed architecture is superior to the centralised baseline by all of the measured metrics. Since the end-to-end latency of the proposed system is lower than that of the centralised one, the density of sensor nodes affects the end-to-end latency of the centralised approach more than that of the proposed system (Fig. 3). This has been mostly due to edge-level preprocessing and local data aggregations at the body coordinator that minimises the transmission delays and network congestion. The energy usage that is demonstrated in Fig. 4 shows that the proposed architecture reduces the per-node energy usage significantly. This is enabled by the adaptive sampling mechanism which enables sensor nodes to modify their transmission behaviour with the remaining energy and therefore the result is a long network lifetime as opposed to a centralised system where the sensor nodes actively transmit raw data. The performance of packet delivery is also stable to change in condition of the channel as depicted in Fig. 5. The suggested system has a better packet delivery ratio compared to the centralised baseline, which indicates the success of wireless traffic reduction and coordinated retransmission-based edge layer.

Scalability analysis will also support the fact that the suggested BASN architecture is reliable in performance despite the increase in sensor node count. In contrast to centralised systems that turn unresponsive due to extreme values of latency and packet loss during dense deployments, the distributed design has graceful performance degradation, and it can therefore be used in long-term and large-scale brain monitoring systems. The proposed architecture is energy efficient and more reliable in terms of communication unlike its rivals in the literature, who have reported centralised wearable monitoring systems previously. The effectiveness of distributed sensing, energy-efficient communication, and edge-based data management is confirmed in these results in an IoT-enabled body area network monitoring multimodal brain.

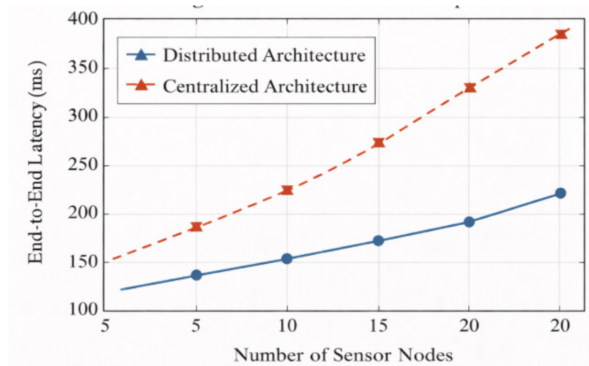

Fig. 3: End-to-End Latency Comparison of Distributed and Centralized BASN Architectures

Comparison of end to end latency of distributed and centralised architectures with respect to sensor node density.

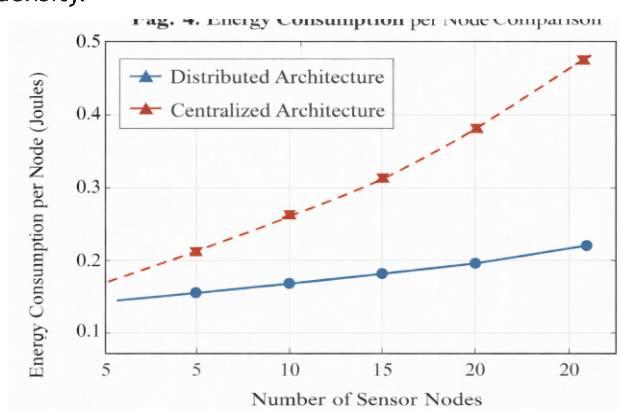

Fig. 4: Energy Consumption per Node in Distributed and Centralized BASN Architectures

Comparison of average energy consumption per sensor node of the distributed and centralised architectures.

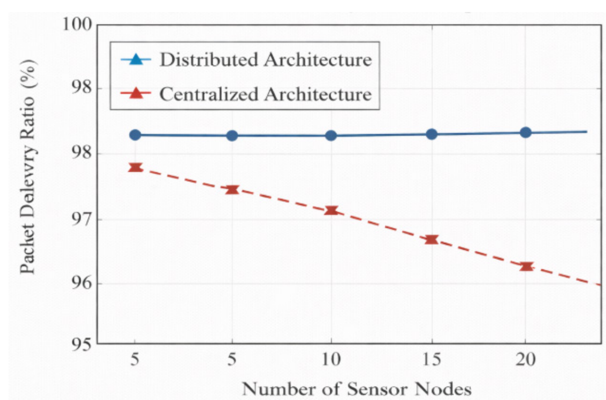

Fig. 5: Packet Delivery Ratio Performance of Distributed and Centralized BASN Architectures

Comparison of packet delivery ratio between distributed and centralised architecture with a growing sensor node density.

Applications and Use Cases

The suggested distributed IoT-enabled body area sensor network (BASN) will be aimed at addressing the continuous, real-time, and energy-saving multimodal brain monitoring in a variety of application fields. The system is capable of delivering reliable functionality at the edge and cloud-aided analytics to be used in both the structured clinical context and the unstructured real-world.

The given architecture allows monitoring brain activity over a long period beyond the four walls of a hospital in remote neurology. The wearable sensor nodes obtain EEG and other physiological data streams on a continuous basis, whereas edge-level preprocessing lowers the high communication cost and maintains longer battery. Aggregated data can be sent to remote healthcare providers to be analysed and early signs of neurological abnormalities are identified and frequent clinical visits are not required to be made.

The system also has a strong support of the assistive technologies in people with disabilities, in which the continuous brain and body monitoring may be helpful in adaptive interfaces and responsive support. The low-latency signal processing, required by real time assistive feedback, and energy-conscious communication of the distributed architecture make it possible to operate the architecture over long periods with frequent recharge requirements.

The proposed BASN would be applicable to measure mental workload level, attention or fatigue level in smart environment (like intelligent workplace or learning spaces) cognitive state assessment. Edge-level processing enables interpreting multimodal streams of data rapidly, and context-sensitive reaction of the system without causing excessive spread of data into the clouds.

Also, the suggested framework facilitates human-machine interaction (HMI) applications, such as brain-computer interfaces and adaptive control systems. Synchronised multimodal sensing combined with a trustworthy wireless communication allows the users and intelligent devices to interact effectively, with the fluctuating conditions of the network.

All in all, the scalable, distributed, and energy-efficient architecture of the suggested BASN allows it to be easily applicable in numerous healthcare and non-healthcare applications, and a versatile basis of future applications of the IoT-enabled brain-monitoring and cyber-physical systems.

Conclusion

In the present paper, an architecture of the distributed Internet of Things (IoT)-based body area sensor network (BASN) in multimodal brain monitoring was introduced. The suggested design focuses on major weaknesses of the traditional centralised monitoring systems, entailing distributed sensing, energy-sensitive communication, and data processing of an edge. The architecture enables to reduce communication risk with edge computations and communication, along with sensor node communication, cloud services, and energy consumption, which involve the alignment of computations and communications, ensuring lower communication latency, network congestion reduction, and reduced energy consumption. An in-depth performance analysis involving simulation was performed to determine the performance of the proposed approach. As the results show, the distributed architecture has lower end-to-end latency, indirect cost per node energy, and improved packet delivery reliability than centralized baselines, especially with an increasing sensor node density. Such advancements validate the appropriateness of the proposed BASN in multimodal brain monitoring in real-time and long-term applications. The proposed system can be implemented in a very broad scope of application domains, specifically in healthcare monitoring, assistive technologies, cognitive state assessment, and human-machine interaction systems due to its modular and scalable design. Moreover, the edge-level preprocessing leads to the integration of weighing down to enhance the system response and simultaneously maintain the energy efficiency needed by wearable devices. The next step in work will be related to implementation of a hardware prototype that will make sure that the proposed architecture is valid in real conditions. The further directions of the research are the introduction of advanced edge intelligence with the help of machine learning methods of adaptive information processing, more complex security measures to maintain privacy, and the analysis of the performance of systems under the conditions of dynamic mobility and heterogeneous networks. These extensions will also enhance the strength and applicability of the suggested IoT-based brain monitoring system.

References

1. Chen, M., Gonzalez, S., Vasilakos, A. V., Cao, H., & Leung, V. C. M. (2011). Body area networks: A survey. *Mobile Networks and Applications, 16*(2), 171–193. https://doi.org/10.1007/s11036-010-0260-8
2. Greco, L., Percannella, G., Ritrovato, P., Tortorella, F., & Vento, M. (2020). Trends in IoT based solutions for healthcare: Moving AI to the edge. *Pattern Recognition Letters, 135*, 346–353. https://doi.org/10.1016/j.patrec.2020.05.016
3. Khan, R. A., & Pathan, A. S. K. (2018). The state-of-the-art wireless body area sensor networks: A survey. *International Journal of Distributed Sensor Networks, 14*(4), 1–19. https://doi.org/10.1177/1550147718768994
4. Latré, B., Braem, B., Moerman, I., Blondia, C., & Demeester, P. (2011). A survey on wireless body area networks. *Wireless Networks, 17*(1), 1–18. https://doi.org/10.1007/s11276-010-0252-4
5. Liu, Q., Mkongwa, K. G., & Zhang, C. (2021). Performance issues in wireless body area networks for healthcare applications: A survey and future prospects. *SN Applied Sciences, 3*, Article 155. https://doi.org/10.1007/s42452-020-04058-2
6. Saleem, S., Ullah, S., & Kwak, K. S. (2011). A study of IEEE 802.15.4 security framework for wireless body area networks. *Sensors, 11*(2), 1383–1395. https://doi.org/10.3390/s110201383
7. Sarma, J., Katiyar, A., Biswas, R., & Modal, H. K. (2019). Power-aware IoT based smart health monitoring using wireless body area network. In *Proceedings of the IEEE 20th International Symposium on Quality Electronic Design (ISQED)* (pp. 1–6). https://doi.org/10.1109/ISQED.2019.8697739
8. Wan, J., Al-Awlaki, A. H., Li, M. S., O'Grady, M., Gu, X., Wang, J., & Cao, N. (2018). Wearable IoT enabled real-time health monitoring system. *EURASIP Journal on Wireless Communications and Networking, 2018*, Article 298. https://doi.org/10.1186/s13638-018-1308-x
9. Wu, F., Wu, T., & Yuce, M. R. (2019). An Internet-of-Things (IoT) network system for connected safety and health monitoring applications. *Sensors, 19*(1), 21. https://doi.org/10.3390/s19010021
10. Wu, T., & Redouté, J.-M. (2017). An autonomous wireless body area network implementation towards IoT connected healthcare applications. *IEEE Access, 5*, 11413–11422. https://doi.org/10.1109/ACCESS.2017.2716344
11. Yeh, K.-H. (2017). A secure IoT-based healthcare system with body sensor networks. *IEEE Access, 5*, 10288–10299. https://doi.org/10.1109/ACCESS.2016.2638038
12. Zohreh, A. B., Navin, A. H. Z., Hosseinzadeh, M., & Rezaee, A. (2020). SENET: A novel architecture for IoT-based body sensor networks. *Informatics in Medicine Unlocked, 20*, 100365. https://doi.org/10.1016/j.imu.2020.100365