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WIRELESS EEG TRANSMISSION AND EVALUATION BASED ON iCLOUD EFFICIENCY: AGE OF TELEMEDICINE

AZMI S. ABDULBAQI[1,*], SAIF ALDIN M. NAJIM[2], FALATH M. MOHAMMED[3], TENDAI MASUNDA[4], ISMAIL Y. PANESSAI[5]

[1,2]College of Computer Science and Information Technology, University of Anbar, Iraq
[3]College of Education for Humanities Sciences, University of Anbar, Iraq
[4]Optical Technology Research Laboratory, Universiti Utara Malaysia
[5]Faculty of Art, Computing and Creative Industry, Sultan Idris University, Malaysia
*Corresponding Author: azmi_msc@uoanbar.edu.iq

Abstract

The World Health Organization (WHO) recommended Cerebral disorders treatment within 90 minutes of the first medical encounter. Where the specialist should recover blood flow to the brain rapidly by injecting intravenous drugs in emergency situations. Tele Encephalopathy Diagnosis includes the use of advanced communication technology to convey to the off-site neurologist the pre-hospital 21-lead EEG signal for early triage, which has been shown to minimize time and overall mortality dramatically. However, hospitals also find the implementation of EEG transmission technologies very difficult to implement. Seven major technological obstacles to pre-hospital EEG transmission are established in the project research, in particular, paramedical discomfort and transport delays; signal noise and processing errors; system failure and communication losses; cellular network reliability; non-compliance with digital EEG format requirements; poor communication with electronic medical records; and cost-effective compliance with digital EEG format requirements. In order to solve both of these technical obstacles, current and potential strategies are studied in detail and contain automatic EEG transmitting protocols; remarkable waveform EEGs; optimal routing strategies; and the cloud computing services utilization instead of vendor-specific processing stations. However, transmission quality management strategies and patient observations are necessary to maintain the primary progress in the application of EEG transmission technologies.

Keywords: Electroencephalogram, Internet cloud (iCloud), Pre-hospital, Telemedicine.

1. Introduction

Within 90 minutes of the first medical experience, the American Stroke Association (ASA) recommends encephalopathy therapy to reduce the total ischaemic duration to less than 2 hours after symptoms begin. One of the best procedures promoted for early encephalopathy diagnosis was by Cerebral Arterial Catheterization (CAC) pre-hospital diagnosis. However, existing attempts to ensure that on-site emergency medical service (EMS) staff discover functional disorders of the brain resulted in high false-positive rates with low precision (~60 per cent), causing in needless and costly activations of CAC laboratories. This has resulted in unnecessary and costly revitalization processes for conventional treatment methods [1]. This includes the shift of the pre-hospital EEG to an off-site neurologist confirmatory diagnosis and a more acceptable case triage. Despite advanced telecommunication technology, sadly, the use of tele-neurology emergency medication is also limited. Therefore, the goal of this analysis is therefore to present a new body of recent development in wireless transmission of EEG; its recent problems and implied solutions; and its clinical influence on patient results [2, 3].

2. Signal Transmission Era

Worldwide hospitals have utilized a different method for transmitting therapeutic EEGs in order to maximize communication and reduce costs, ranging from a traditional telephone, fax and internet utilization to more innovative and modern techniques. Since the neurological consultant knew the profiles and clinical specifics of patients, effective utilization telephone transfer systems between patient care centres could help enhance medical identification and triage procedures before the current EEG period. However, the accuracy of these transmitted EEGs has always been questionable, with fewer than 80 % of patients reported to be of acceptable quality [4, 5]. Owing to enormous growth in the concepts of wireless digital EEG transmission, it became cost-effective though, this method in pre-hospital settings was limited. The digital EEG is preferred a wirelessly transmitted in its digital original format to the destination (receiving) site to be handled (processed) for optimum usefulness (Fig. 1) [6, 7].

For the purposes of the initial evaluation of the patient's condition, a 21-lead EEG signal is obtained through leads tied to the scalp and transmitted After these signals are converted to digital formatting via the EEG modem to a remote compatible receiving station utilizing a cell phone network [8]. EEG data is decoded by the receiving station, EEG printing for analysis purpose, and/or sends these signals in the image form or data form to the off-site neurologist's mobile phone (or email). There have been tremendous problems with several recent attempts to introduce such a wireless EEG transmission concept [9]. This involved camera mobile phone utilization to photograph EEG prints and send an image to a treating neurologist's mobile device or email in a multimedia document. In addition to the resultant simple and irrelevant technological factors of severe content degradation. However, compared to the transmission of the entire EEG image, the transmission of actual data is technically superior. The smaller the size of the data transmitted, the greater the speed of transmission, the higher the performance and the lower the cost [10, 11].

3. Contemporaneous Challenges and Potential Solutions

A wireless EEG transmission comes with many obstacles, even with the most advanced networking technologies. Several critical technological caveats that need to be resolved in order to optimize the therapeutic advantages of EEG in tele-neurology have been identified by a systematic analysis of the literature. Including their proposed remedies, a description of these concerns [12, 13].

4. Medical Services Transport Delay

In emergency cases, slow response and delay in transferring the patient to the emergency department may endanger the patient's life [14]. Where paramedics sometimes need more time for training purposes in locating the patient, as well as locating the 21-lead on the patient's head so that skin-to-skin contact with the scalp in order to capture EEGs signal to be of high quality without noise [15].

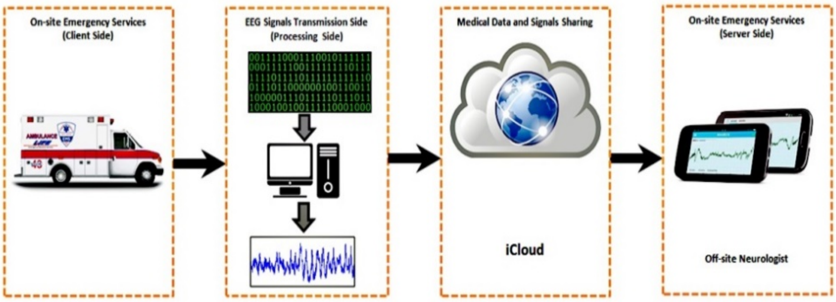

Fig. 1. EEG wireless transmission of the Pre-hospital based on Icloud.

A domestically founded 24/7 international hub for remote EEG analysis and patient triage proved to have a realistic and successful impact on the outcomes of patients with neurological disorders [16]. In outpatient telemetry monitoring and remote control of patients with implantable devices [17], the introduction of wireless EEG transmission by EMS staff appears to be lagging behind the introduction of related technologies and services. EEG transmission in these environments is regularly carried out using dedicated mobile technologies or smartphones for general purposes. [18]. This delay in the introduction facilities the emergency setting that may involve low economic benefits and higher hazards and liabilities for link failure or compromised or low-quality data that may be blurred or deleted [19]. A proposed method has been developed for the purposes of transmitting EEGs Signal collected to the hospital in order to reduce the burden on EMS staff and to avoid the problems of delaying transportation time, which led to a reduction in the neurologist's time in assessing the patient's condition [20].

5. Interpretation of Noisy EEG Signal

Some studies indicate that fewer errors can be made utilizing print EEG compared to digital EEG, other experiments indicate that the quality of perception efficiency is the same for both. This refers to the quality of EEGs signal recorded and transmitted, as studies refer to that only 70% of real-time EEG operations sent by

EMS are of high quality, and 80% of these signals are suitable for diagnostic assessment [21, 22]. It is possible to facilitate the neurologist's off-site interpretation of EEGs by enlarging the high-resolution EEG image [23, 24].

6. Hardware Failure and Signalling Transmission Failure

In about 18 percent of all patients, pre-hospital EEG transmission failures occur. These are due to the failure of the receiving station cellular link (28 percent); transmitting system contact error (12 percent); problematic mobile phone system (10 percent); network failures (7 percent); delayed EEG visualization on the off-site cell phone of the neurologist (6 percent); inadequate emergency network coverage (6 percent); or other unspecified caution [25]. The satellite communications utilization may solve network error problems especially in urban areas as well as solve poor coverage in rural areas [26]. There are several benefits to utilizing the automated system: (1) Give neurologists a continuous alert in case they are outside their work site by transmitting the EEG signal; (2) Provide necessary annotations for EEG signals; and (3) Send a decision on sorting to activate the CAC lab has the potential reform of the problems associated with screening decisions and delayed perception [27, 28].

7. Security of Cell Phones Networks

The optimal routing utilization may increase the efficiency of the transmission protocol for every specified EEG data receiver. The utilize of nationwide satellite coverage to support tele neurology also has the possibility to develop the reliability and reduce congestion of networks [29, 30].

8. Failure to Follow Digital EEG Format Requirements

Amid global attempts to standardize digital EEG formats (e.g., SCP-EEG), there are many manufacturers that still utilize several vendor-specific EEG data extraction instruments and algorithms for the desired usage of 21-lead computer-based EEGs. The non-compliance of manufacturers with these requirements results in different clinical EEG formats when hospitals utilize multiple EEG means, reducing the feasibility of standardizing the EEG processing at the destination station (Receiving) [31]. Theoretically, a cloud-based framework that can read numerous EEG data formats has the potential to improve clinical practice. In addition, an internet-cloud infrastructure it will be available from everywhere, enabling the introduction of regional and possibly national EEG transmission network coverage [32, 33]. Many other solutions are proposed to connect mobile devices and internet servers (clouds) with such networks and medical information sharing. One potential alternative is to build an Omni SQL (Structured Query Language) database to communicate on cell phones with PACS to currently download medical images and translate EEGs based on waveforms into DICOM. The principal components transferring, or EEG key indicators derived from compressed waveforms or compressed waveforms is another solution that permits for more lean and efficient data transmission. In addition, it permits accurate and customized analysis of serial EEG data [34, 35].

9. E-Medicinal Records Integration

EEGs signal is viewed based on signs, medical records, and results of other diagnostic tests, and not considered separately. Off-site neurologists are frequently left to triage patients with a single EEG, resulting in 6%-16% lacking diagnosis of cerebral disorders that are mentioned to a hospital regional [36]. The accuracy without clinical information of a professional neurologist reading the EEG has not been well checked and neurologists can appear to over-read EEGs, results in high false-positive rates.

Optimum integration between the notified EEG and the hospital e-medical record systems for prompt consultation, even in the event of an emergency, is required for both of these purposes [37, 38]. A well-defined challenge is the convergence of distributed EEGs with medical information, but it still presents a concern for several hospitals. It is notable that the range of this concern goes beyond technological viability, but also includes provisions of the Health Insurance Portability and Transparency Act (HIPTA), which include improved aspects of device security and privacy protection [39, 40].

10. Pre-requisite Implementation of Costly Hardware

Pre-hospital EEG signal transmission also involves the expensive installation of provider hardware and software, because the heterogeneity of vendor EEG formats restricts service access, especially in remote areas. This has prompted several researchers to utilize comparatively affordable EEG transmission methods, including the utilization of digital cell phone cameras, leads to many technological caveats restrict the full potential of high-quality EEG transmission signal processing [41]. In order to combine various forms of EEG data utilizing the Internet, the previously mentioned cloud-based infrastructure can be utilized in limited-access zones to digital technologies, this is beneficial in achieving cost savings and rapid implementation of EEG transport technology [42].

11. Medical Effects of Early Dissemination of EEG

Cerebral disorders are the leading reason for adult visits in the emergency department between different countries with approximately 5 million yearly visits [43]. In Cerebral patients, the effect of pre-hospital diagnosis of early encephalopathy and overall death rate is clear. On average, wireless delivery of 21-lead EEGs to off-site neurologists decreases encephalopathy by 50 minutes and 50 percent decrease in encephalopathy and 55 deaths per 1,000 patients with neurological disorders (Table 1) [44]. This is particularly important because: (1) 7%-22% of patients with cerebral disorders aged 45-60 years are atypically present where pre-hospital diagnosis can play an important role; (2) Roughly one-third of diagnoses of cerebral disorders due to night-time, are delayed/weekend patients presenting where a pre-hospital diagnosis can invalidate the influence of "time of day and day of the day" [45, 46]. Pre-hospital EEG therefore has the ability to (1) shorten CAC and shorten the duration of stay for patients with cerebral disorders; (2) increase access to specialist services, minimize excessive referrals and reduce costs; and (3) play an important role in correctly stratifying the risk of different clinical populations [47],

Table 1. The impact of pre-hospital cerebral disorder diagnosis utilizing 21-lead EEG CAC period and mortality in general.

Researchers and Year	ED Detection (Diagnosis)			Pre-hospital Detection (Diagnosis)			Effect on Findings	
	n	CAC	Death rate	n	CAC	Death rate	Δ CAC	Δ death rate
Lemesle et al. [46]	136	55 min	4.0%	226	22 min	5.0%	− 48 min	3.0 %
Rachim et al. [47]	54	126 min	–	51	87 min	–	− 42 min	–
Majumdar and Ward [48]	50	119 min	7.0%	92	64 min	1.1%	− 54 min	− 5%
Lee et al. [49]	216	153 min	33.0%	460	94 min	18.0%	− 58 min	− 13%
Lou et al. [50]	89	112 min	–	146	51 min	–	− 60 min	–
Kumar et al. [51]	271	84 min	9.5%	139	50 min	4.0 %	− 37 min	− 5.7%
Liu et al. [52]	44	105 min	–	123	57 min	–	− 51 min	–
Weighted Total	716	110 ± 27	12.9%	1,234	61 ± 24	8.0%	− 52 min	− 5.5%

ED: Emergency *Department; CAC: Cerebral Arterial Catheterization time; Δ: net change*.

12. The Future of Tele Neurology

When neuroscience is applied accurately remotely, it improves the quality of brain data sent from one end to the other; Confirmed to improve access to consultant neurologists off-site; Improving emergency and pre-hospital management depends entirely on the correct diagnosis, and this diagnosis in turn provides real-time EEG data for the purpose of diagnosing brain function. There are many systems that have been developed and improved, including smart systems. There are various examples must be noted; EEG acquisition station with telecommunications portals for immediate messaging and real-time video; a computer that looks like a cell phone business card to track smart real-time brain function; and a portable, sensing hat, 21-lead EEG system with a network of BT for surveillance patient wirelessly. However, most the clinical centres, including hospitals will need implement their own quality guarantee systems to track the efficacy of communication and patient findings. These systems are required to deliver initial admission in EEG transmission technology implementation.

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