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EPILEPTIC SEIZURE DETECTION IN IOHT: A VISUAL IMAGE-BASED PROCESSING APPROACH

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ABSTRACT

This paper presents a new technique for electroencephalography (EEG) seizure detection from multi-channel EEG signals based on image processing concepts in Internet-of-Health-Things (IoHT) systems. The multi-channel EEG segments are treated as two-dimensional matrices as if they were images. Scale-space analysis with Scale Invariant Feature Transform (SIFT) is used to extract the feature points in the up-mentioned two-dimensional matrices. The number of points is used as a discriminating factor between seizure segments and normal segments. An exhaustive study of the 24 patients of the Children's Hospital Boston (CHB-MIT) database is presented in this paper. The EEG signals are transmitted via WiFi/Bluetooth, then all their signals are segmented into one-second segments, the numbers of features points are extracted from these segments, the Probability Density Function (PDF) of the number of feature points for normal and seizure segments are estimated. The Equal Error Rate (EER) is estimated between PDFs of the numbers of feature points in seizure and normal segments. Simulation results on all patients reveal the ability of the proposed technique to set a patient-specific discrimination threshold of 70% of Max spectral power for seizure detection with an accuracy of 95.6%.

Keywords: *Electroencephalography (EEG); Scale Invariant Feature Transform (SIFT); IoHT; Epileptic Seizure detection; Visual image processing.*

1. INTRODUCTION

Many definitions of "epilepsy" in the literature exist; at least there are four different proposals of the International League Against Epilepsy (ILAE) referring to "epilepsy". The most recent definition of epilepsy is "Epilepsy is a disorder of the brain characterized by an enduring predisposition to generate epileptic seizures and by the neurobiological, cognitive, psychological, and social consequences of this condition" [1-4]. Epilepsy has the same meaning as "seizure disorders". It is worth noting that epilepsy ranks fourth in terms of the most common neurological diseases. Epilepsy has many types affecting different ages and causing many health problems [5]. A seizure is caused by sudden, abnormal, and excessive electrical activity in a group of brain cells. Seizures start when the nerve cells send wrong or distorted signals that ignite patients with distressing feelings, which makes them acting strangely, usually as a spasm or a violent vibration involving their muscles [6, 7].

Seizures accompanied by temporary symptoms. These symptoms include loss of consciousness or awareness, disturbances of movement, loss of sensation or cognitive functions such as vision, hearing and taste, and others. It varies from one patient to another, it depends on the location where the brains' disturbance first starts, how long it continues, and how far it spreads. The ILAE released a new classification of seizures in 2017, it depends on clinical causes rather than pathogenic cases; the new classification consists of three classes: Focal onset, Generalized onset, Unknown onset. A Focal seizure is a seizure that begins in an area or groups of cells in one brain side. A focal aware seizure or simple partial seizure is a seizure that happens during awake and aware. It will have called focal impaired awareness seizure or complex partial seizure if it happens during confusion or unconsciousness. Generalized onset seizures are seizures that happen when areas or group of cells on both brain sides are affected. An unknown onset seizure is the seizure that has an unknown location of the beginning, or the seizures have no available information, it may be diagnosed as a focal or generalized when more information is gathered later [8- 11].

Although there is no cure for epilepsy permanently, it can be controlled largely by medicines, or by using smart tools. Otherwise, surgical intervention is required immediately. According to WHO, up to 70% of seizure cases can be completely controlled successfully with anti-epileptic drugs (AEDs). However, in some cases when seizures last for long periods, or when it is repeated at high rates without consciousness in between, it is diagnosed as a medical emergency.

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Applications of computer vision and artificial intelligence became very touchable and widely used. The field of smart health care has developed tremendously, accompanied by the development of many emerging technologies, especially in the field of the Internet-of-Things (IoT). The Internet-of-Health-Things (IoHT) has emerged as an effective way to save the lives of individuals in many diseases, especially epilepsy cases. Many seizure detection algorithms and methods are developed in IoHT; it is a smart system that consists of sensors, transmitters, network medium, processor, storage unit, and application [12]. The paper includes significant novel technique as it presents applying a new proposed approach for effective seizure detection using the SIFT algorithm on IoHT systems, making use of its provided highly discriminative feature descriptor. The proposed approach using SIFT algorithm succeeded efficiently in seizure detection, it achieved low EER and FAR.

2. Literature Review

The analysis of human brain activity is very important for better understanding and diagnosing related diseases. Seizure duration usually lasts from thirty seconds to two minutes in most cases, doctors use brain scans and other diagonal tests including blood tests and medical history to detect and diagnose seizures. The electroencephalogram (EEG) is a detecting process of the brain’s electrical activity using an electrical measuring device called electrodes. The electrode is a flat and small metal tool, connected to the brain scalp. EEG is one of the main diagnostic measures for epilepsy. The brain cells send electrical signals continuously. These signals are classified to the delta, theta, alpha, beta, and gamma according to their frequency range, which spans from 0.1 Hz to more than 100 Hz. EEG records are the main source for investigating seizure epilepsy; EEG records are still rich and have more information to be revealed, it has a big amount of valuable data [13].

Most algorithms of seizure detection have two main stages; first, features extraction of EEG brain records through an appropriate quantitative method. Next, a classification criterion is applied; this criterion may be a modern machine-learning algorithm or a simply applied threshold that differentiates seizures from normal intervals [14- 16]. A survey of EEG seizure detection techniques based on the processing domain was presented by Alotaiby et al. (2014). They classified seizure detection methods to time-domain methods, frequency-domain detection algorithms, wavelet domain, Empirical Mode Decomposition (EMD), Principal Component Analysis (PCA), Singular Value Decomposition (SVD), and Independent Component Analysis (ICA) domain. Most detection techniques adopt time-domain or wavelet-domain algorithms [17]. Massoud, et al. (2019) introduced a comparison of detection techniques for human feature points, the comparison shows that the Laplacian of Gaussian (LoG) technique has the most quality [18].

Dey, et al. (2017) proposed a reliable ECG monitoring system, they developed a low cost and improved Zigbee wireless unit [20]. Daoud, et al. (2018) introduced a seizure detection system using EMD with Deep Neural Network in [21]. Park, et a. (2018) presented a seizure detection model using Spatio-temporal correlation and Convolution Neural Network in [22]. Kaur (2021) proposed a wireless body area network using Castalia Simulator in [19], the system relied on a medium access control layer and was characterized as low cost and low power consumption. Sundaravavidel, et al. (2018) developed a low-cost nutrition monitoring system using the deep learning method in [23]. Yuan, et al. (2018) introduced a seizure detection system using wavelet-transform context fusion in [24]. Sayeed, et al. (2019) introduced an accurate seizure detection system using machine learning, they developed an Edge-Device for seizure detection [25, 26]. Dolgin, (2020) introduced a seizure detecting smartwatch that alerts healthcare providers in [27]. Olokodana, et al. (2020) presented a real-time automatic seizure detection system using DWT with the Kriging model in [28].

This paper proposes a new model using the Scale Invariant Feature Transform (SIFT) algorithm in a visual image-based manner; the SIFT algorithm is applied on transmitted EEG records to identify and distinguish the time of disturbances from normal intervals.

3. Methodology

Our proposed system consists of a "cap" that collects EEG signals, the cap is supported by a group of compact, ultra-low power sensor that collects data. The collected EEG signal is transmitted via Wifi/Bluetooth to a smartphone application or any wearable device "watch". Next, a feature extraction stage of EEG segmented frames, a threshold-based classification process, and finally, the application sends the data for a continuous monitoring system at emergency vehicles, smart hospitals, family members, or any healthcare service provider, as shown in Fig. (1). The processing stage uses the sift algorithm, which is an AI system that detects the EEG status, takes decisions, sends information to those involved, and updates records.

As shown in Fig. (2). First, the transmitted signals are sent via Bluetooth to the mobile application. Next, the signal is segmented into fixed time length windows, the windowing process output is a segmented signal, which is

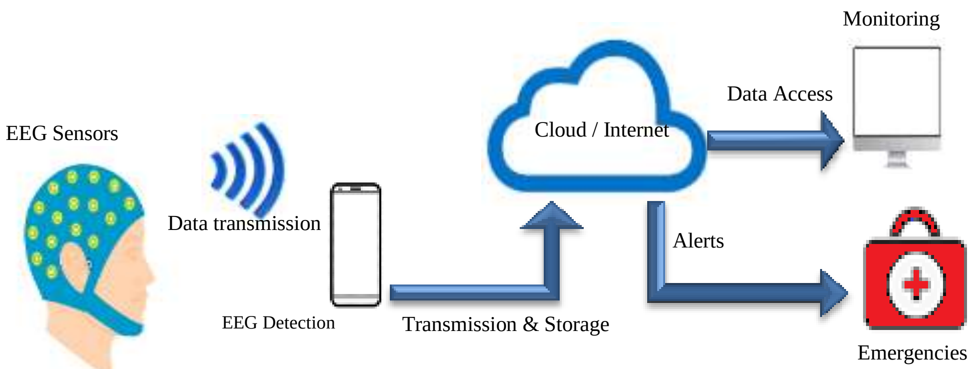


Fig. 1. The proposed architecture

treated as an image, it represents features of seizure time. The SIFT is used as a feature descriptor for images, it extracts abstract features from a local point in the image; these features are extracted to represent the information around this point by representing the information in a features vector or features descriptor. The approach is based on using the SIFT to detect regions of seizures in the segmented frame of EEG signal and differentiate these periods from the normal signals. Decisions are taken according to an applied threshold, then the data is sent to a cloud server where records are updated, and a monitoring system is watched. This is a very cost-effective solution where cloud-based monitoring systems are also available.

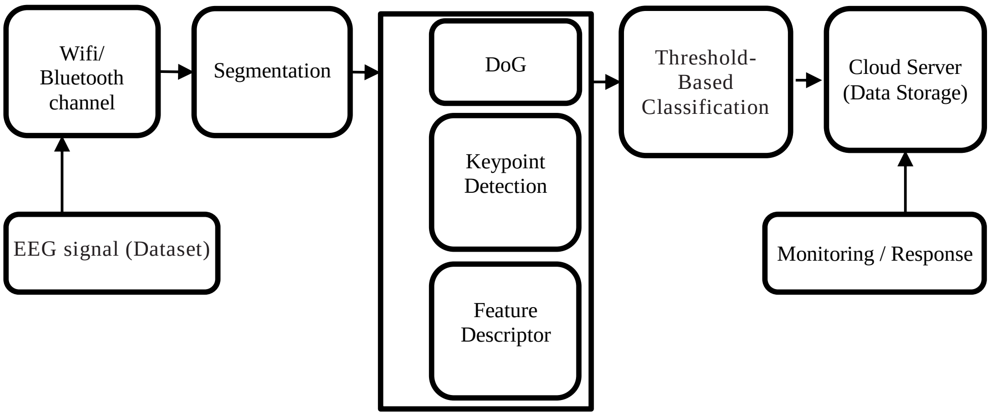


Fig. 2: Block diagram of the proposed technique.

The objective of using SIFT for features representation is to produce a highly discriminative signature of the seizure signal, which experimented as a local image trying to make it more distinctive as possible from normal brain signals. In the proposed approach SIFT algorithm encodes interesting information in the brain signal into a series of numbers and act as a sort of numerical point "fingerprint". Consequently, the numerical point is used to differentiate one signal feature from another. Finally, this information is used to detect seizure time; these intervals could be easily differentiated from the normal periods. The approach makes use of SIFT advantages for feature description.

a. Scale-Invariant Feature Transform (SIFT) algorithm

The SIFT algorithm was published by David Lowe, University of British Columbia Canada in 1999; SIFT extracts features in a feature descriptor whose features remains unchanged when the transformation is applied. It remains invariant to changes in scale, illumination, blur, and local affine distortions. Besides, it is easy to extract, highly distinctive, and has a low error probability when used for object identification. SIFT includes both feature detection and feature description, SIFT only refers to feature descriptor, while the term "SIFT key point" is usually used to indicate the detected feature. Fig. (3) shows the most popular and frequently used image feature descriptors. There are many other techniques, but not shown here for space limitation [29-30].

In the proposed approach, SIFT algorithm is applied to the segmented frames, the number of interest keypoint is calculated using the Difference of Gaussians (DoG), a feature vector is composed for each keypoint using a scale, orientation, and location parameters. The local orientation of the image is calculated over several scales and over neighborhoods around the point of interest using the local image properties to provide invariance against rotation. Finally, the feature descriptor is calculated based on the detected information of each key point.

i. Scale-Space Representation

SIFT operates on a Gaussian scale-space to achieve scale invariance, this is achieved by convolving the original image with gradually increased Gaussian variances. The Gaussian convolution of the input image $I(x,y)$ with Gaussian blur $G(x,y,k\ \sigma)$ at scale $k\ \sigma$ (σ is the standard variance); $D(x,y,k\ \sigma)$ calculated as:

$$D(x,y,\sigma) = G(x,y,k\ \sigma) \times I(x,y) \quad (1)$$

Thus, a set of convolved images $\{G(x,y,\sigma i),i=1,2,...,n\}$ can be used to denote the Gaussian scale space of the original image I, σ is increased gradually by a constant factor k, $\sigma i+1=k\ \sigma i$. SIFT takes the extrema in the DoG scale space as the initial keypoint, to be robust to scale changes and with high repeatability. To achieve this, the DoG scale space is constructed by subtracting adjacent scales of the image:

$$Ds(x,y,\sigma) = D(x,y,k\ \sigma) - D(x,y,\sigma) \quad (2)$$

Thus, to apply Difference of Gaussians (DoG) function to the series of smoothed and resampled images in scale space, a DoG image $DG(x,y,\sigma)$ is:

$$DG(x,y,\sigma)=Ds(x,y,ki\ \sigma) - Ds(x,y,kj\ \sigma) \quad (3)$$

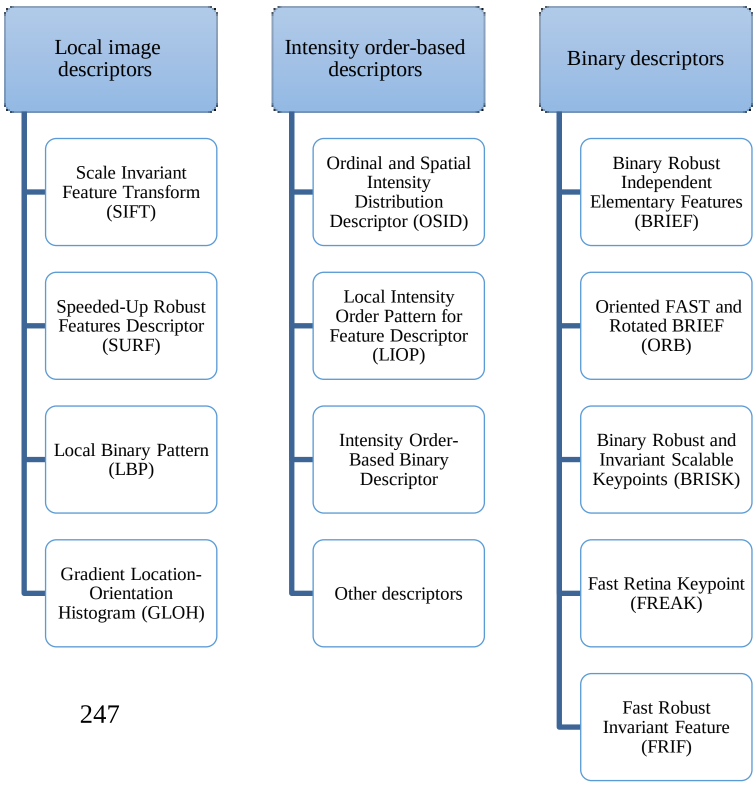


Fig. 3: The popular image feature descriptors.

ii. Keypoint features selection

The maxima and the minima of the result define the key locations. Low contrast and edge points are discarded to achieve recognition stability and better matching. These key points are stored to be indexed, and the high probability nearest neighbours' points are identified using the Best-bin-first (BBF) algorithm. Each pixel in the DoG images is compared to its eight neighbours at the same scale and 18 corresponding neighbouring pixels in the above and below neighbouring layer (nine in each of them).

The close and unstable local extrema are suppressed using non-maximum suppression, (i.e. if the pixel value is the maximum or minimum among all compared pixels, it is selected as a candidate key point). This is a variation of one of the methods developed by Lindeberg [31]. The best-bin-first (BBF) algorithm limits searching after the first 200 nearest neighbour candidates, this helps speed up search and results in no more than 5% loss of correct matches while eliminating 90% of false matches. Hessian matrix H is computed at the key point location and scale [32]:

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{yx} & D_{yy} \end{bmatrix} \qquad (4)$$

iii. Features Selection Mechanism

The SIFT algorithm begins by sampling the magnitudes and orientations of the image gradient in a region of 16×16 around each key point, a local descriptor is constructed to describe the key point in a scale and rotation-invariant manner using each detected keypoint parameter including position, scale, and orientation [33,34]. The local region defined by the above parameters is divided into 4×4 grids sub-region that contains eight orientation pins in each as shown in Fig. (4), to compute histograms of gradient orientations in these grids.

Finally, to form a set of orientation histograms, all histograms are concatenated together to form a 128-dimensional descriptor (4×4 histograms each with eight bins, producing a feature vector of 4×4×8=128 element per keypoint). These concatenated histograms are normalized to gain invariance to affine changes in illumination as a final step producing a unit vector as the SIFT descriptor [35].

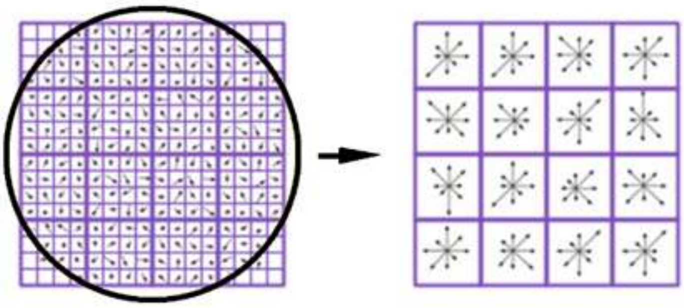


Fig. 4: Mechanism of the SIFT features for a 16×16 pixel and a 4×4 array.

The methodology of the proposed approach can be detailed as follows: First, EEG records are transmitted via Bluetooth. Next, EEG signals of multi-channel natures are segmented into one-second segments, taking every 256 samples as one segment (window size of one second) to obtain the spectral features in this period.

After obtaining the spectral features, DoG is calculated to construct a scale-space for each segment. Then, applying the Hessian matrix to detect the keypoints, and estimate the number of feature points. The next step is the estimation of PDFs for No. of feature points across signals. Finally, the estimation of the discrimination threshold and equal error rate (EER).

An electroencephalographic scalp database containing brain records was used for different patients with epileptic seizures; the database was recorded at the Children's Hospital Boston (CHB-MIT) database, available online [36]. The records duration is more than 40 hours per most cases, it is divided into an hour for recording. It shows abnormalities of brain signals before, during, and after these episodes. The data files saved in the European Data Format (EDF format) were captured in 23 channels with a sampling rate of 256 Hz, the detailed information shown in Table 1.

Table.1: Detailed statistics extracted from CHB-MIT database (Values in seconds)

Patient ID	N	Total duration	Min. Duration	Max. duration
Chb01	7	442	27	101
Chb02	3	172	9	82
Chb03	7	402	47	69
Chb04	4	378	49	116
Chb05	5	558	96	120
Chb06	10	153	12	20
Chb07	3	325	86	143
Chb08	5	919	134	264
Chb09	4	276	62	79
Chb10	7	447	35	89
Chb11	3	806	22	752
Chb12	40	1475	13	97
Chb13	12	535	17	70
Chb14	8	169	14	41
Chb15	20	1992	31	205
Chb16	10	84	6	14
Chb17	3	293	88	115
Chb18	6	317	30	68
Chb19	3	236	77	81
Chb20	8	294	29	49
Chb21	4	199	12	81
Chb22	3	204	58	74
Chb23	7	424	20	113
Chb24	16	511	16	70

4. Analysis

Extensive simulation experiments have been performed for all patients, the SIFT algorithms were applied to the transmitted records. First, the segmentation process is achieved by applying a window size of one second, taking 256 samples per segment. The DoG is calculated to construct a scale-space for each segment. Next, the Hessian matrix is applied and the number of key points is calculated for each segment during the seizure epileptics periods; this number is compared to the number of key points during normal periods. The change in the signal component during epileptic seizures is quantified to provide useful information; the PDFs are calculated versus the number of

SIFT points for both seizure epochs and normal segments. Receiver Operating Characteristic curves (ROC curve) are calculated, also. It is a plot of the true-positive rate against the false-positive rate for the different possible cutpoints of a test.

Table.2: FAR, FRR, and EER

ID	L	FAR	FRR	EER
Chb01	100	6.02E-04	0.89	0.0036
Chb02	100	0.0076	0.9946	2.21E-04
Chb03	100	1.46E-04	0.9259	0.0018
Chb04	100	9.74E-04	0.9831	6.45E-04
Chb05	100	7.92E-05	0.9628	0.0019
Chb06	100	0.0237	0.9783	1.20E-22
Chb07	100	0.0110	0.9352	6.32E-04
Chb08	100	6.16E-05	0.9793	0.0013
Chb09	100	0.0254	0.9503	0.0019
Chb10	100	0.0136	0.8115	0.0044
Chb11	100	0.2706	0.9495	8.41E-04
Chb12	100	0.0386	0.7382	0.0054
Chb13	100	0.0991	0.8563	0.0462
Chb14	100	0.0379	0.8655	0.0130
Chb15	100	0.0028	0.9647	0.0014
Chb16	100	0.0273	0.8277	0.0036
Chb17	100	0.0063	0.8738	0.0030
Chb18	100	0.0097	0.9195	2.76E-04
Chb19	100	0.0219	0.9607	0.0017
Chb20	100	0.1800	0.8610	0.0662
Chb21	100	0.0294	0.8411	0.0043
Chb22	100	0.0220	0.9642	0.0010
Chb23	100	0.0048	0.8075	0.0033

Fig. (5) to Fig. (9) show ROC curves for randomly selected patients, figures reveal the PDFs for No. of SIFT points for seizure and normal segments. For these, it is clear that a threshold estimation process is possible. Accuracy, Equal Error Rate (EER), False Accept Rate (FAR), and False Reject Rate (FRR) values are calculated as an evaluation criterion for a set of L points; results are tabulated in Table 2. As shown from statistics in Table 2, Low EER values reveal a high ability to detect seizures efficiently.

Table.3: Comparison of the existing seizure detection methods.

Work	Method	Accuracy
Park et al. [7]	Spatio tempral Correlation & CNN	85.6%
Yuan et al. [9]	WT-Ctx-Fusion	95.7%
Olokodana et al. [12]	DWT with Kriging model	93.4%
Current approach	SIFT-based visual approach	95.6%

Accuracy of combined data = 95.60%, Table 3 shows the accuracy comparison of the existing seizure detection methods for the same database; Park et al. achieved an accuracy of 85.6% by applying Spatiotemporal Correlation & CNN [7], Yuan et al. [9] used WT-Ctx-Fusion to achieve an accuracy of 95.7%, and Olokodana et al. [12] used a DWT with Kriging model to achieve accuracy of 93.4%. The proposed SIFT-based visual approach achieved accuracy of 95.6% with an applied threshold of 70%; this is almost equal to the WT-Ctx-Fusion approach, which put the SIFT-based approach on the top set of recommended techniques in EEG detection in IoHT systems.

$$Accuracy = \frac{No.\ of\ accurately\ classified\ images}{Total\ No.of\ images} \times 100 \qquad (5)$$

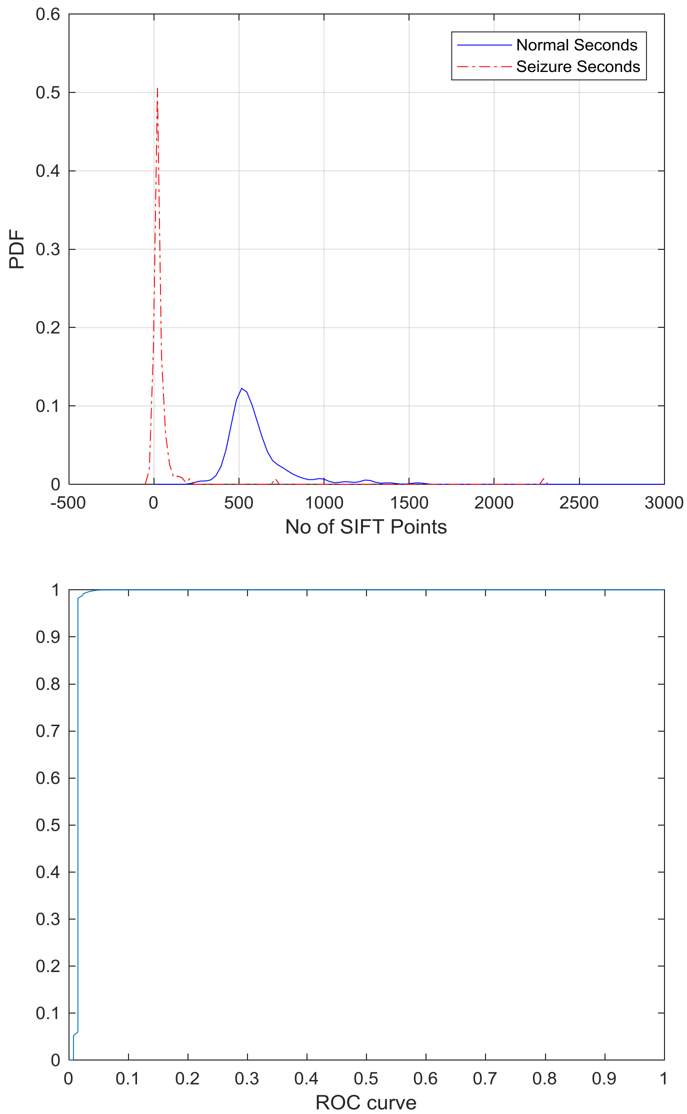
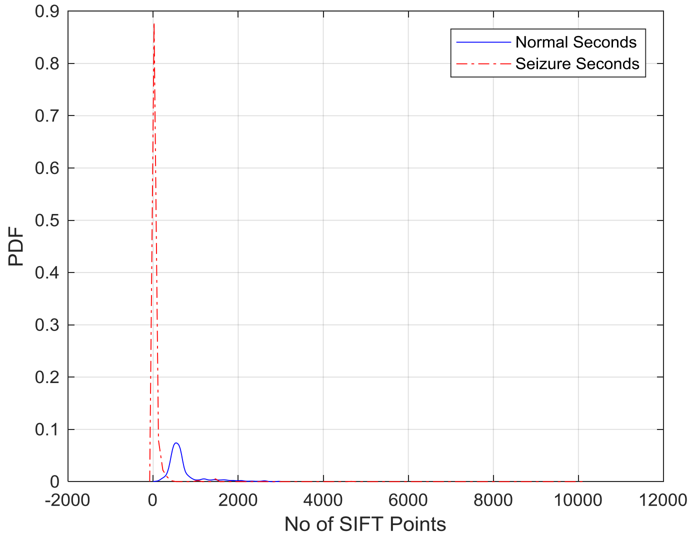


Fig. 5. Patient 2 and ROC curve.



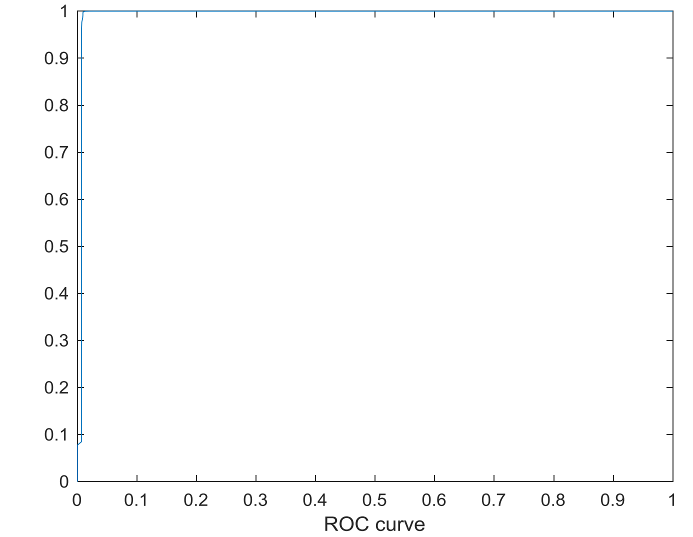


Fig. 7. Patient 5 and ROC curve.

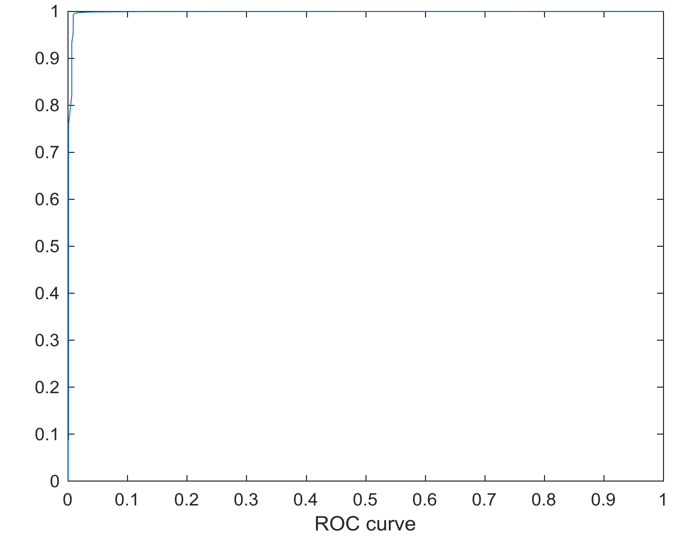
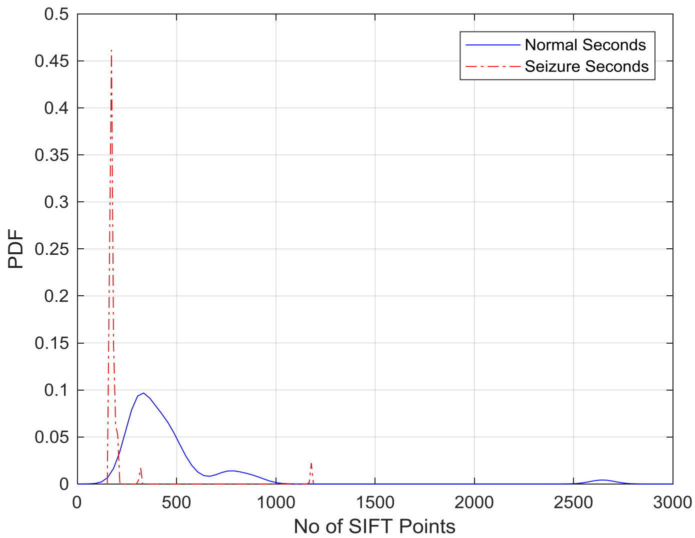
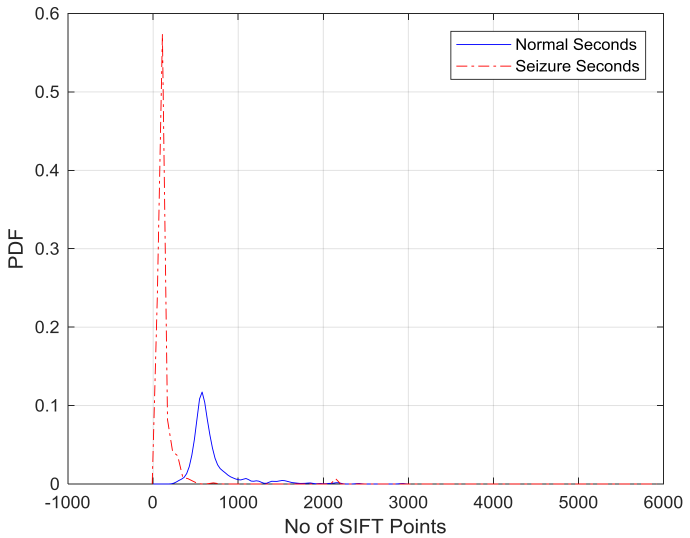


Fig. 6: Patient 3 and ROC curve.





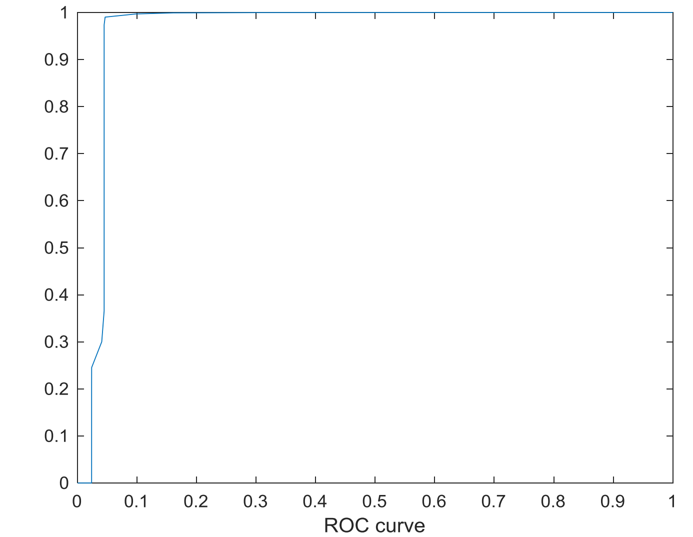


Fig. 8. Patient 6 and ROC curve.

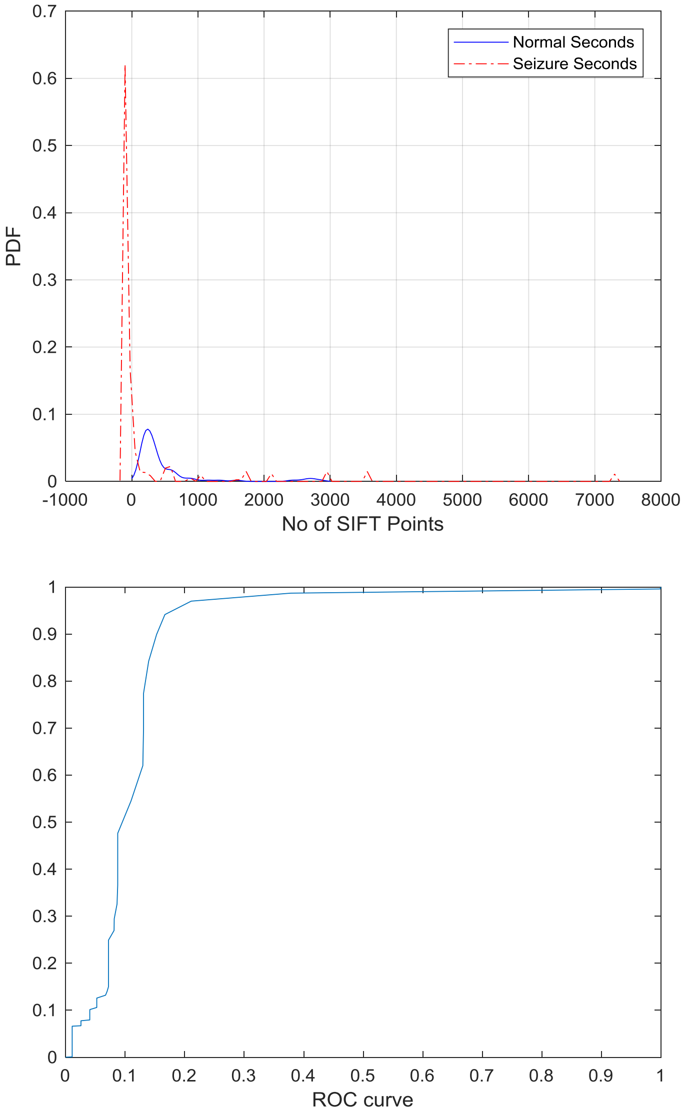


Fig. 9. Patient 7 and ROC curve.

CONCLUSIONS

This paper revealed that it is possible to deal with the multi-channel EEG transmitted segments in IoHT systems as if they are images. It is possible to apply 2-D feature extraction methods like SIFT to discriminate between seizure and normal activities during the seizure detection process. The proposed approach uses the SIFT descriptor algorithm adopted in image processing for an accurate visual representation of seizures. The basic idea of the approach is to represent the different activity levels of transmitted EEG signals as images. Next, the scale-space analysis is used to analyze these images for anomaly detection. The analysis is used to localize the seizures on the charts and represent EEG signal records. Experiments conducted with CHB-MIT database of 24 patients, 198 seizures, a total duration of approximately 3.23 hours, and more than 990 hours of recorded data. Simulation results revealed a high success rate for the detection of epileptic activities in the proposed approach. Results show that the number of SIFT points could be used easily to detect seizure intervals and differentiate them from normal brain signals making use of the provided highly discriminative feature descriptor. The proposed approach using the SIFT algorithm succeeded efficiently in seizure detection in IoHT systems achieving an accuracy of 95.6%.

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كشف نوبات الصرع في أنظمة انترنت الأشياء الصحية: طريقة معالجة قائمة على الصورة المرئية

الملخص:

تقدم هذه الورقة البحثية تقنية جديدة لاكتشاف النوبات من خلال تخطيط كهربية المخ من إشارات (EEG) متعددة القنوات بناءً على مفاهيم معالجة الصور في أنظمة إنترنت الأشياء الصحية .(IoHT) حيث يتم التعامل مع مقاطع EEG متعددة القنوات على أنها مصفوفات ثنائية الأبعاد كما لو كانت صورًا. ويتم استخدام تحليل مساحة النطاق باستخدام Scale Invariant Feature Transform (SIFT) لاستخراج النقاط المميزة في المصفوفات ثنائية الأبعاد المذكورة أعلاه. يتم استخدام عدد النقاط كعامل تمييز بين مقاطع النوبة والأجزاء العادية. يقدم البحث دراسة شاملة لـ 24 مريضًا من قاعدة بيانات مستشفى بوسطن للأطفال(CHB-MIT) حيث يتم إرسال إشارات مخطط كهربية الدماغ لاسلكياعبر WiFi / Bluetooth ، ثم يتم تقسيم جميع إشاراتها إلى مقاطع مدتها ثانية واحدة ، ويتم استخراج عدد النقاط المميزة من هذه الأجزاء ، وكذلك دالة كثافة الاحتمالية (PDF) لعدد النقاط المميزة للفترات العادية والنوبة. يتم حساب القطاعات وكذلك يتم تقدير معدل الخطأ المتساوي (EER) بين ملفات PDF لعدد نقاط المعالم في النوبات والأجزاء العادية. تكشف نتائج المحاكاة على جميع المرضى عن قدرة التقنية المقترحة على تعيين حد تمييز خاص بالمريض بنسبة 70٪ من الطاقة الطيفية القصوى لاكتشاف النوبات بدقة تبلغ 95.6٪.