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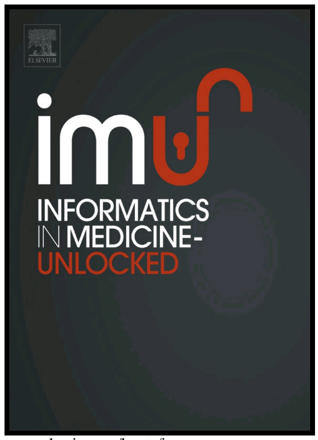

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Advances in Biomedical Signal and Image Processing – A Systematic Review

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Abstract

Biomedical signal and image processing establish a vital area of specialization in both academic as well as research aspects of biomedical engineering. The concepts of signal and image processing have been extensively used for extracting the physiological information in implementing many clinical procedures for sophisticated medical practices and applications. In this paper, the relationship between electrophysiological signals, i.e., electrocardiogram (ECG), electromyogram (EMG), electroencephalogram (EEG) and functional image processing and their derived interactions have been discussed. Examples have been investigated in various case studies such as neurosciences, functional imaging and cardiovascular system, by using different algorithms and methods. The interaction between the extracted information obtained from multiple signals and modalities, seems to be very promising. The advanced algorithms and methods in the area of information retrieval based on time-frequency representation have been investigated. Finally, some examples on algorithms have been discussed in which the electrophysiological signals and functional images have been properly extracted and have a significant impact on various biomedical applications.

Keywords:
Biomedical signals and images; Processing; Analysis.

1. Introduction

Biological and medical information processing is a dynamic field of natural science for a while [1]. The biomedical signals have been used by the architects for designing the bioelectrical and biomechanical systems. The physicians and human services experts introduced the diagnosing procedures of medical issues. The biomedical signal has been handled earlier to focus on design or diagnosis. The existing signal processing tools/programs is more suitable for engineers functioning in biomedical applications, according to their position they can utilize the tools/programs easily [2]. The biomedical signals are considered as more important such as action potential and event-related potential. Electromyogram (EMG), electroneurogram (ENG), electrocardiogram (ECG) and electroencephalogram (EEG) are existent action potential. The event-related potentials (ERPs) are electrogastrogram (EGG), phonocardiogram (PCG), carotid pulse (CP), signals from catheter-tip sensors, speech signal, vibromyogram (VMG), vibroarthrogram (VAG), oto-acoustic emission signal [3]. The various image modalities are widely used in biomedical field, i.e., functional magnetic resonance imaging (fMRI), computed tomography (CT), ultrasound imaging and positron emission tomography (PET) [1]. The fMRI data produces high spatial resolution functional data and comparatively low temporal resolution, which have been generally used to study the working of healthy and diseased brain, under different task conditions and under rest [4]. Meanwhile the computed tomography associated with anatomy, which provides the spatial and temporal resolution [5].

In ultrasound imaging techniques, 2D techniques have been used for assessing the plaque morphology, since insufficient image contrast and variation in 2D ultrasound examination may affect the accurate assessment of morphological plaque change. Hence 3D techniques were developed for improving the visualization and quantification of complex anatomy and pathology.

Image processing techniques includes several methods namely enhancement, segmentation, detection of region of interest, pre-filtering method, thresholding technique and morphological operations. Segmentation is a process that is used for eliminating the complex procedures in images. The information from texture, shape, contours, etc., is used in the classical image segmentation [6]. Edge detection is a technique used to find boundaries of objects inside an image. An edge is defined as sudden discontinuities in an image. A sudden change in brightness level within an image can be termed as an edge. Different first derivative and second derivative edge detectors are Sobel, Prewitt, canny Robinson and Laplacian. Image enhancement techniques used to restore the original image either in space domain or frequency domain. The space domain approaches are point processing and mask processing.

The various types of biomedical signals and images can be measured by particular sensors. The processing of biomedical system explained with several steps such as (i) Acquire the relevant biomedical information using sensors, (ii) Pre-processing can be done after acquisition, (iii) Followed by filtering and feature extraction techniques to establish the condition of biomedical system and (iv) The last step seems to be classification and diagnostics, where the normal and abnormal samples were decide the status of result [1].

The aim of this systematic review is give attention to biomedical signal and imaging fusion procedures because of their importance in the medical field. Therefore, the paper is systematized as; Section 2 particularizes the methodology of the literature. Section 2.2 describes the basic transforms that are often used in the fields of cardiology and neurosciences. Section 2.3 explains the common algorithms of signal and image fusion techniques. In Section 3, discusses the overview of transforms used and some examples associated with fusion techniques.

2. Methodology

The basic transforms and algorithms that are often used in the fields of cardiology and neurosciences are explained in this section. It includes the transforms such as Fourier, Fast Fourier transform, wavelet transform, Laplace transform, curvelet transform, wavelet packet decomposition, Hilbert transform, Hadamard transform and warblet transform.

2.2 Overview of Transforms used in Biomedical Signal and Image Processing

Gutiérrez-Gnecchi et al. [7] propounded a method to classify the arrhythmia implemented on a digital signal processing platform (DSP). The wavelet transform based on quadratic wavelets algorithm is used for identifying ECG waves and fiducial marker array. The arrhythmia classification was done by probabilistic neural network. The classification includes 5 step process, Cardiac frequency calculation, RR interval measurement, P wave measurement, PR interval measurement and QRS complex measurement. The wavelet transform is represented in a mathematical notation (Eq. (1)). The transform include four scale values corresponds to a bandwidth: 62-125Hz, 18-60 Hz, 8-26 Hz and 4-13 Hz. The first three scales were used for detection of R peaks. Local maximum and minimum values were used to detect Q and S waves with the limit of 30%. The P and T waves were detected by fourth scale. The probabilistic neural network distributes the probability of arrhythmia. The authors [8-11] used the wavelet transform to detect the QRS complex wave from the acquired ECG signal.

$$W_f(u,s) = f * \varphi^*_{u,s} == \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{s}}\varphi^*\,(t-u/s) \quad (1)$$

where s is the scale factor and $\varphi^*_{u,s}$ is the mother wavelet.

To estimate the realistic geometry from body surface potentials a spline Laplacian (SL) ECG algorithm was proposed by He et al. [12]. The introduced estimation algorithm linked with the parameters of spline Laplace. Taking inverse of general matrix given the formulation of spline Laplace. Among the parameters, one is needed to estimate the realistic geometry surface from body surface potentials. This algorithm is furthermore scrutinized in computer simulations to authorize this approach in spherical volume conductor, where the feasibility of mapping cardiac electrical sources, heart torso-model was tested. The conductivity of the torso volume conductor is mentioned as 1.0. To simulate the noise contaminated body surface potentials Gaussian white noise (GWN) associated with the different noise levels were used. It has been reported that the conventional five-point local Laplacian estimator performs the SL and give local based Laplacian ECG estimation [13]. Babiloni et al. [14] proposed a system that strongly reports, that the SL algorithm efficiently implements the realistic geometry spline in EEG based studies.

Jero et al. [15] applied curvelet transform for hiding information of patients' ECG signals. To apply this method, the ECG signal is decomposed into frequency sub-bands. The patient information is secured by quantization approach. The transform is based on scales, where four scales were represented in this study. The co-efficient of this four scale computation is expressed in a (Eq. (2)).

$$C^D(j,l,k) = \sum_{n1,n2\in P_j} \hat{f}\,[n1, n2 - n1\tan\theta]\widetilde{U_j}[n1,n2]e^{i2\pi(\frac{k_1 n_1}{L_{1j}}+\frac{k_2 n_2}{L_{2j}})} \quad (2)$$

Using zero threshold value the ECG steganography based on curvelet transforms was evaluated. The curvelet transform also used to decompose the image into frequency sub-bands to the number of scales [16].

The wavelet packet method has been developed by Bian et al. [17]. Their method is utilized for finding the steady state visual evoked potential (SSVEP). The normalized power from special sub-wavebands was detected by this method. This is considered as a feature vector for the linear classifier. The SSVEP is an input signal of brain computer interface (BCI). The wavelet packet decomposition method is the extension of wavelet transform. It splits the bands into two for low and high frequencies. The sub-waveband width for scale 4 is expressed in (Eq. (3)).

$$(n-1)2^{-5}f_s \leq fn2^{-5}f_s,\ \text{n=1,2,L,16} \quad (3)$$

where F_s is the sampling frequency and n is the number of sub-waveband.

The authors used ten subjects (6 men and 4 women) for their experiment. The BCI system was used to detect the non-evoked and evoked EEG signals. After pre-processing method the data was handled by wavelet packet decomposition to obtain the normalized power of 16 sub-wavebands. Then they compared the method with conventional FFT for performance measures. It is stated that the Hilbert-Huang transformation and phase locking method of SSVEP are also better than the FFT method [18,19].

One optimal combination method for detecting the R peaks in ECG consists of Hilbert transform with the adaptive thresholding method. The noise presented in the signal was removed by the discrete wavelet transform in both time and frequency domain. The authors denoted the Hilbert transform of the signal in (Eq. (4)) [20].

$$z(t) = H[y(t)] = \frac{1}{\pi}\int_{-\infty}^{\infty} y(\tau)\,\frac{1}{t-\tau}\,d\tau \quad (4)$$

where $y(\tau)$ is the time function.

Hilbert transform acts like a linear filter, there is no change in spectral component amplitudes but changes occurs in phase values. The maximum amplitude was identified to detect the R peaks by the adaptive thresholding method.

Conjugate symmetric- complex Hadamard transform (CS-CHT) was used for detecting the atrial fibrillation (AF) in ECG features [21]. The complex Hadamard transform matrices were expressed in (Eq. (5-7)).

$$H_s = \begin{matrix} H_{s/2} & H_{s/2} \\ H'_{s/2}T_{s/2} & H'_{s/2}T_{s/2} \end{matrix} \tag{5}$$

$$\text{Where } T_s = \begin{matrix} H'_{s/4} & H'_{s/4} \\ H'_{s/4}I'_{s/4} & -H'_{s/4}I'_{s/4} \end{matrix} \tag{6}$$

$$I'_{s/2} = \begin{matrix} I_{s/4} & 0 \\ 0 & -I_{s/4} \end{matrix} \tag{7}$$

The feature extraction techniques used the different orderings like natural, Paley, sequency and Cal-sal. The Levenberg-Marquardt neural network classifier was used for approximation and it also detects the atrial fibrillation.

Kazemi et al. [22] depicted bootstrap-based generalized warblet transform for vital sign extraction in heart and respiratory monitoring radar system. This method uses the kernel and it is estimated using iteration procedure to produce the instantaneous frequency of the radar system. The backscattered radar produced the heart and respiratory information, where time-frequency representation was obtained by this signal.

Another method is picture evaluation and music signal extraction based on two-dimensional de-trended fluctuation analysis (DFA) and two-dimensional fast Fourier transform (FFT) [23]. These methods are used for finding pleasant photographs and generating music. Result from this method to picture evaluation has the fluctuation function which is used to compute the slope of the plot, where F(s) represented in (Eq. (8)).

$$F(s) \sim \alpha_d^s \tag{8}$$

where α_d is the scaling component.

The three cases $\alpha_d \leq 0.75$ (random image), $0.75 < \alpha_d \leq 1.25$ (1/f noise) and $\alpha_d > 1.25$ (Brownian) were used to classify the pictures.

However the use of the 2D FFT the music can be generated and used to reflect the feature of image. The frequency level $F_j(Hz)$ of the music is expressed in (Eq. (9)).

$$F_j = \begin{cases} 440 \times 2^{j-\frac{46}{12}} & \text{, if j} = 1,2,\ldots,96, \\ 0, if\ j = 0 \end{cases} \tag{9}$$

The authors analysed the 198 photographs using one-dimensional FFT algorithm in their previous study [24].

A method proposed by Manandhar et al. [25] is measurement of primary tip vibration excursion. They described an algorithm stroke by Fourier transform (SRYFT) for this measurement so that it can be used for reducing manual error and operator deviation. The major advantage of this method is high speed measurement without operator training. From the microscopic image, the two-dimensional Fourier transform is calculated for this measurement. The peak separation in Fourier domain can be considered as a method to estimate the tip excursion. The algorithm SRYFT is represented in (Figure 1). Fourier transform has the significance of insensitive to phase also the results combined with all the pair points to form the motion blur.

The stationary wavelet transform (SWT) method non sub-sampled contourlet transform (NSCT) can be efficient to improve the shift variance, directionality and phase information in fused image. The images were acquired from two different imaging sensor modalities [MRI and CT- scan [26]. To minimize the redundancy, principal component analysis algorithm can be used in SWT domain. Maximum fusion rule can be used in NSCT domain for extracting the diagnostic features. The two transforms used to increase the performance of medical images supporting fusion. The comparative study of the included transforms used in biomedical signal and image processing shown in Table 1.

2.3 Established Algorithms on Electrophysiological Signals and Functional Imaging

In recent years, there has been a growing interest in the use of biomedical signal and image processing.

Mjahad et al. [27] proposed a detection method of ventricular fibrillation and tachycardia from surface ECG using classifiers. The time-frequency representation images were given directly to the classifier as an input. Logistic regression with L2 regularization (L2 RLR), adaptive neural network classifier (ANNC), support vector Machine (SSVM), and bagging classifier (BAGG) the four classifiers were used in this study. In addition, this method could be robust when compared to feature selection and extraction methods. The AHA and MIT-BIH databases were utilized for evaluation study. Windows reference marks are calculated for the time-frequency representation. Wigner ville variant distribution was adapted for time-frequency representation.

Non-ischemic dilated cardiomyopathy is diagnosed using the right ventricular long axis strain (RV-LAS) measurement. This right ventricular long axis strain (RV-LAS) axis used to measure the displacement in tricuspid annulus. This measurement uses four approaches to obtain different reference values such as RV-LAS Ins/peri, RV-LAS Ins/mid, RV-LAS left ventricular (LV)apex/peri and RV-LAS LVapex/mid. The RV-LAS Ins/peri approach measures the length between insertion point of right ventricular (RV) and LV also lateral insertion of tricuspid valve. RV-LAS Ins/mid used to measure the length between insertion point and middle of line connecting the tricuspid valve. RV-LAS LVapex/peri measures the LV apex and lateral insertion of tricuspid valve length. The final approach RV-LAS LVapex/mid used to measure the LV apex and the middle of line connecting the tricuspidal valve [28]. The RV-LAS is calculated using the formula represented in (Eq. (10)).

$$RV - LAS = \frac{length_{endsystole} - length_{enddiastole}}{length_{enddiastole}} \times 100 \qquad (10)$$

To detect the different facial expressions, EEG was recorded with facial electromyography. Early posterior negativity was enhanced at the range of 200-280ms. Spontaneous zygomatic activity was enhanced at the range of 500-750ms [29]. At the range of 250ms the EMG changes occurred for faces, and then for 500ms in scenes. It is stated that faster response occurred in facial expressions and weaker response at neural activity. The authors [30,31] well documented the neural activity of emotional faces and emotional scenes were extracted from the authors

[32,33].The different neural activities were demonstrated at P1 and N100/N170 components for picture and word-primed recognition.

The hemodynamic changes in interictal epileptic discharges (IED) were represented by the fusion of EEG and fMRI analysis shown in (Figure 2). To identify the irritative area in IED, a method EEG source imaging (ESI) was used. This method used to improve the blood oxygen level dependent (BOLD) signal. Then, the region of interest (ROI) is defined which consists of five ESI neighboring solution points nearby the maximum density. Then, this is implemented in LAURA source localization algorithm because of the local dependency constraint [34]. Finally, the average ROI density was identified using the continuous ESI function analysis.

The self-regulation of slow cortical potentials (SCP) method was proposed by Hinterberger et al. [35] that aim to prevent the epileptic seizures in addition to link with paralyzed patients. The fusion of BCI and fMRI were used to the investigation of SCP. The four step processes were used in this study such as; training of SCP, SCP feedback in fMRI environment, functional imaging and artifact handling. The self-regulation of SCP monitored by the EEG and fMRI which allows to correlates the local BOLD responses and SCP changes.

The muscle functional magnetic resonance imaging technique was used to investigate the neck muscle pain with the activation of cervical flexor muscles during craniocervical flexion (CCF). 14 healthy subjects were used to determine the activity of longus colli (Lco), longus capitis (Lca) and sternocleidomastoid (SCM) muscles at three cervical levels of (C0eC1, C2eC3 and C6eC7). Both rest and measurement of CCF with and without induced pain of upper trapezius conditions were analyzed [36].

Suprascapular nerve injury associated with muscle injury is discovered by the magnetic resonance neurography (MRN). The MRI correlated with the EMG results was obtained from this method. In this study, the acute injury, subacute injury and chronic injury were classified for patients. The time period of the acute injury is mentioned as 1-2 weeks. The time period of subacute injury is 3-4 weeks and for chronic injury is more than 4 weeks [37].

Sulayman et al. [38] explained the semi-automatic detection and segmentation of cerebral saccular aneurysms (CSAs) in 2D digital subtraction angiography (DSA) images. The 2D and 3D images were used in [39-41] for detection and classification of cerebral saccular aneurysms. The Otu's method used in [38] for thresholding in image segmentation. To refine the segmentation process, morphological process of eroding the binary image was started. The false positive aneurysms were detected and then classified by rule based classification.

To evaluate the intervertebral discs magnetic resonance imaging (MRI) seems to be a standard noninvasive imaging modality [42]. Mok et al. [43] proposed three approaches to explain nucleus pulposus (NP) and annulus fibrosus (AF) on MRI images. The authors applies the three different region-of-interest (ROI) drawing methods, i.e., (i) radiologist-guided manual ROI (M-ROI); (ii) five square ROIs which consists of 20% of the midline disc diameter (5-ROI); and (ii) From anterior to posterior seven square ROIs placed horizontally (7-ROI) to define NP and AF. The Intra-class correlation coefficient (ICC) and Blande Altman plot were used to explain the three approaches results. Among the three approaches the authors recommended the M-ROI method to segmentation of AF and NP for time being.

Rudea et al. [44] proposed a method to segment the medical ultrasound (US) imaging using fuzzy connectedness framework. They used the local phase approach and feature symmetry which is used for segmentation. The studies related to local phase included various methods, i.e., segmentation [45,46], registration [47], image enhancement [48], tissue characterization [49] and feature detection [50] were demonstrated. In [44] the fuzzy connectedness framework method is applied to 81 US images of the fetal arm, similarly studies included for the fetal head [51], the fetal femur [52], and the fetal abdomen [53].

The comparative study of included algorithms on electrophysiological signals and functional imaging is shown in Table 2.

3. Discussion

The systematic review shows the overview of transforms used in biomedical and image processing. A comparative study between these commonly employed transform produces a clear knowledge about the advances in biomedical signal and image processing. In addition, the wavelet transform [7], Laplace transform [12], Curvelet transform [15], Hilbert transform [20], Warblet transform [22] and Hadamard transform [21] to help in extracting the features of ECG. The extension of wavelet transform, i.e., wavelet packet decomposition method can help to extract the features of EEG [17].

The ECG signal is extensively deliberated as an important diagnostic signal in assessment of the cardiovascular system. EEG is heavily used diagnostic signal in assessment of the central nervous system (CNS). EMG is an electrical signal used in the assessment of the muscle movement [1] Varieties of established studies on electrophysiological signal and functional imaging have been stated. Models based on imaging techniques have also helped to recognize the methods of image processing, i.e., segmentation [38,44] and enhancement [48].

The segmentation process is being automatic or semi-automatic. Among the many image segmentation methods the fuzzy connectedness (FC) frame work can used to discover the fuzziness in ultrasound images [44]. This method also is used to myocardial segmentation process includes the contrast-enhanced ultrasound images and intravascular ultrasound images. Several segmentation algorithms can be used to detect the intracranial vessels and aneurysms, i.e., pattern recognition, model-based approaches, tracking-based approaches, artificial intelligence-based approaches and hybrid approaches. However these algorithms have the following limitations like expensive and need user interaction to initialize. So the semi-automatic segmentation of CSA from 2D DSA images were used [38]. This method performs a smooth segmentation.

As mentioned in Section 1 and Section 2.3, one of the major challenges in the medical field is fusion process of biomedical signal and imaging techniques. The fusion techniques still need development to acquire more details and gain more access to the body organs. The fusion techniques include the electrophysiological signals such as ECG, EEG and EMG in this review. Feature selection is one of the major aspects in the process of biomedical signal and image processing. In ECG the features are derived from morphology through direct or indirect method in time or frequency domain. To avoid the complexity of this feature selection method the time-frequency representation images were directly feed to classifiers as input [32]. The BCI technique is used to communicate the brain waves into computer. Few algorithms have been used to investigate the BCIs for detecting non-evoked and evoked potentials [17] and use to detect the epileptic seizures [35]. The BOLD response in EEG gives the brain metabolism with high spatial resolution, where the fMRI is used to provide this information. In this study, the BOLD response used to activate the self-regulation of SCP without feedback [35]. As well as the

BOLD signal could be improved by continuous EEG source imaging in the interictal epileptic activity [34].

The magnetic resonance imaging seems to be a major technique to detect the skeletal muscle pathological conditions. The changes are occurred by muscle signal intensity that is traumatic, inflammation and neurologic conditions [37]. The neck pain [36] and nerve injury [37] was discovered by this magnetic resonance imaging.

4. Conclusion

Biomedical signal and image processing constitutes different interests in the educational and research field in biomedical engineering. With the enhanced physiological knowledge, a wide assortment of innovative works in clinical methods makes use of this concept in the medical applications. Further, advanced algorithms investigated in the signal and image processing field most often carried out by time- frequency representation approaches in the field of neurosciences, functional imaging and cardiovascular system. In the advanced world, some of the imaging modalities are now widely accessible, that can deal with the exposition of disease and provide diagnostic information.

The fusion of electrophysiological signal and imaging techniques is a salient approach in the medical field. This systematic review provides a several well-established algorithms based on the fusion of electrophysiological signal and functional imaging. The presented case studies introduced a narration of ECG, EEG, EMG signals and imaging fusion steps due to the importance of this technique in this context. The future investigation is comparing the performance of most advanced algorithms and methods using the fusion of electrophysiological signal and functional imaging.

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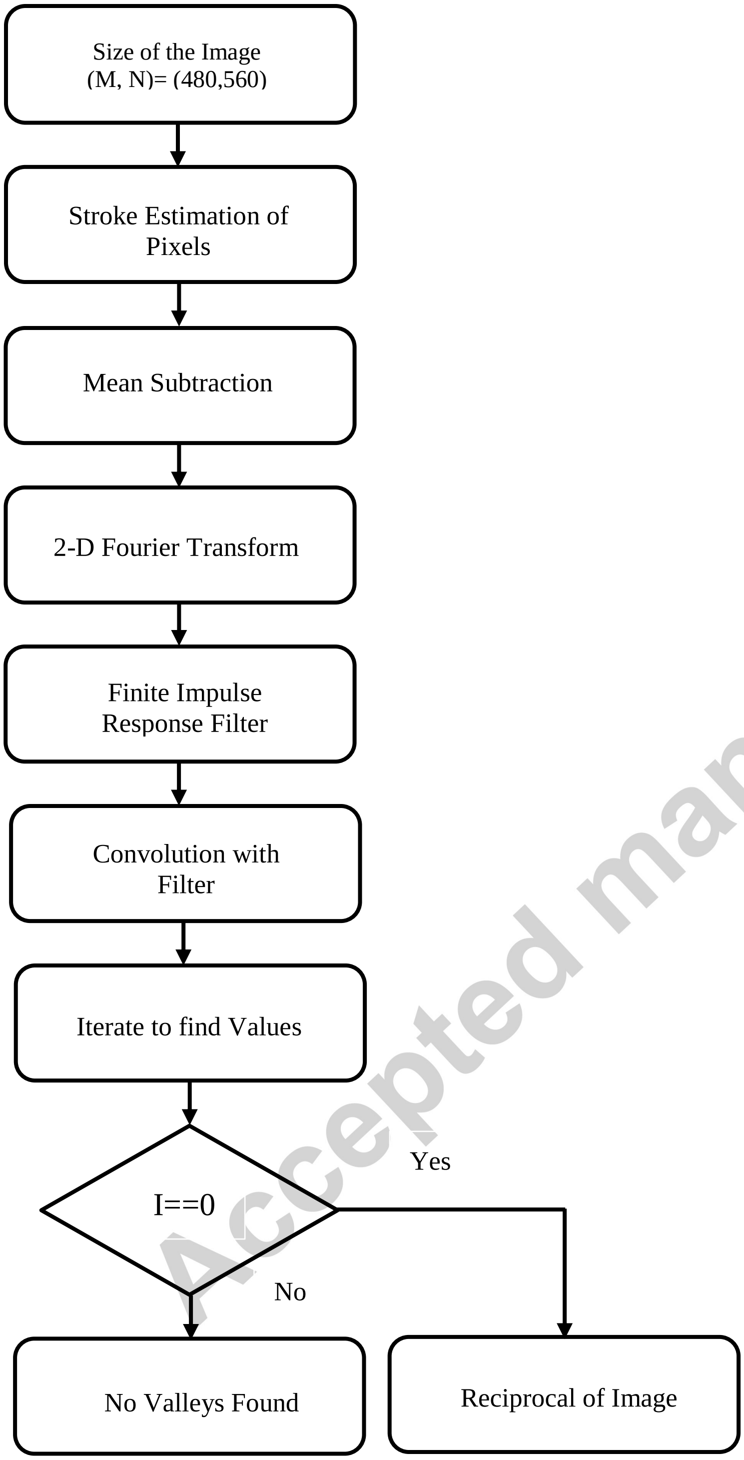

Figure 1: Flowchart representation of stroke by Fourier transform (SRYFT) algorithm. (Adapted from Manandhar et al. [25])

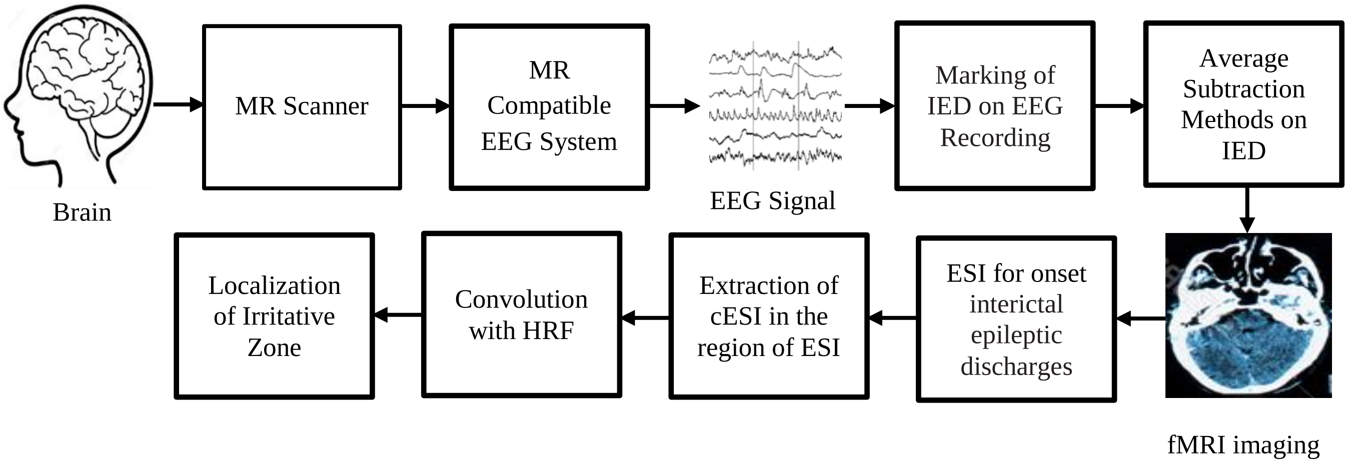

Figure 2: Fusion process of EEG signal and fMRI imaging for localization of irritative zone in pre-surgical epilepsy cases. Interictal epileptic discharges (IED), Electrical source imaging (ESI), Continuous electrical source imaging (cESI), Hemodynamic Response Function (HRF)

Table 1: Comparative study of included transforms used in biomedical signal and image processing.

Authors	Transforms	Purpose of Study
Gutiérrez-Gnecchi et al. [7]	Wavelet transform	Arrhythmia classification from ECG signal
He et al. [12]	Laplace transform	Realistic geometry estimation from body surface potentials (ECG)
He et al. [14]	Laplace transform	Realistic geometry estimation from body surface potentials (ECG)
Jero et al. [15]	Curvelet transform	Information protection of patients' ECG signal
Bian et al. [17]	Wavelet packet decomposition	Detection of non-evoked and evoked potentials from EEG signal
Sahoo et al. [20]	Hilbert transform	Detection of R peak from ECG signal
Annavarapu et al. [21]	Hadamard transform	Detection of atrial fibrillation from ECG signal
Kazemi et al.[22]	Warblet transform	Extraction of vital sign (heart rate, respiratory rate)from ECG signal

Table 2: Comparative study of included algorithms on electrophysiological signals and functional imaging.

Author	Algorithms	Disorder
Mjahad et al. [27]	ECG and time-frequency representation images	Detection of Ventricular fibrillation and tachycardia
Arenja et al. [28]	ECG and functional magnetic resonance imaging	Diagnose the non-ischemic dilated cardiomyopathy
Vulliemoz et al. [34]	EEG and functional magnetic resonance imaging	Diagnose the interictal epileptic discharges
Hinterberger et al. [35]	BCI and functional magnetic resonance imaging	Prevention of epileptic seizures
Vagnie et al. [36]	EMG and functional magnetic resonance imaging	Detection of neck muscle pain
Hassanien et al. [37]	EMG and functional magnetic resonance imaging	Detection of muscle injury