IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 7, 2021, accepted August 20, 2021, date of publication August 24, 2021, date of current version September 2, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3107371

An Efficient Gabor Walsh-Hadamard Transform Based Approach for Retrieving Brain Tumor Images From MRI

K. VENKATACHALAM[1], SIULY SIULY[2], NEBOJSA BACANIN[3], STEPAN HUBÁLOVSKÝ[1], AND PAVEL TROJOVSKÝ[4]

[1]Department of Applied Cybernetics, Faculty of Science, University of Hradec Králové, 50003 Hradec Králové, Czech Republic
[2]Institute for Sustainable Industries & Liveable Cities, Victoria University, Melbourne, VIC 14428, Australia
[3]Department of Informatics and Computing, Singidunum University, 160622 Belgrade, Serbia
[4]Department of Mathematics, Faculty of Science, University of Hradec Králové, 50003 Hradec Králové, Czech Republic

Corresponding author: Pavel Trojovský (pavel.trojovsky@uhk.cz)

This work was supported by the Excellence Project PřF University of Hradec Králové (UHK) under Grant 2208/2021–2022.

This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

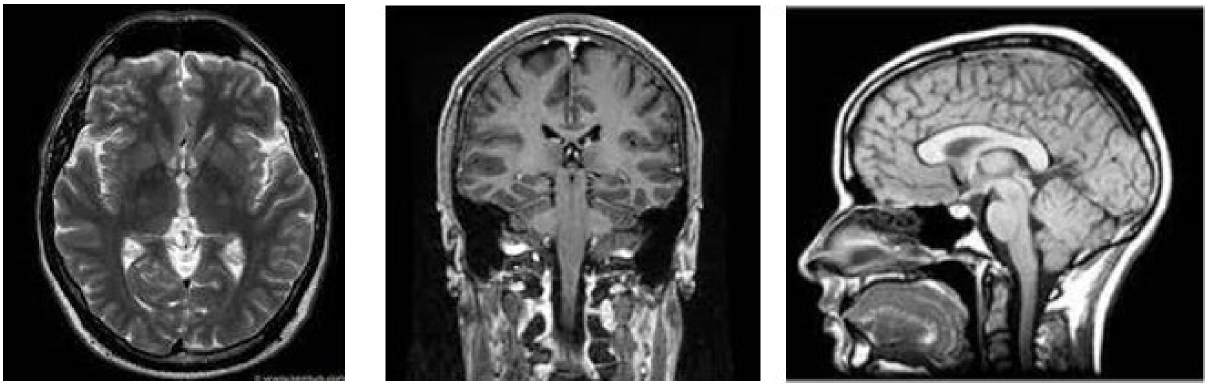
ABSTRACT Brain tumors are a serious and death-defying disease for human life. Discovering an appropriate brain tumor image from a magnetic resonance imaging (MRI) archive is a challenging job for the radiologist. Most search engines retrieve images on the basis of traditional text-based approaches. The main challenge in the MRI image analysis is that low-level visual information captured by the MRI machine and the high-level information identified by the assessor. This semantic gap is addressed in this study by designing a new feature extraction technique. In this paper, we introduce Content-Based Medical Image retrieval (CBMIR) system for retrieval of brain tumor images from the large data. Firstly, we remove noise from MRI images employing several filtering techniques. Afterward, we design a feature extraction scheme combining Gabor filtering technique (which is mainly focused on specific frequency content at the image region) and Walsh-Hadamard transform (WHT) (conquer technique for easy configuration of image) for discovering representative features from MRI images. After that, for retrieving the accurate and reliable image, we employ Fuzzy C-Means clustering Minkowski distance metric that can evaluate the similarity between the query image and database images. The proposed methodology design was tested on a publicly available brain tumor MRI image database. The experimental results demonstrate that our proposed approach outperforms most of the existing techniques like Gabor, wavelet, and Hough transform in detecting brain tumors and also take less time. The proposed approach will be beneficial for radiologists and also for technologists to build an automatic decision support system that will produce reproducible and objective results with high accuracy.

INDEX TERMS Hough filter, Gabor filter, glioma brain tumour, soft computing techniques, Walsh-Hadamard transform.

I. INTRODUCTION

Brain tumors are one of the biggest killers of children and adults under 40 worldwide. A brain tumor is a cluster of abnormal cells that grow out of control in the brain. People with a brain tumor experience a variety of physical symptoms including headaches, vision problems, seizures, memory loss, changes in personality, difficulty in concentration, loss of coordination and changes in speech, loss of balance and mood swings. There are two types of brain tumors: cancerous (malignant) and noncancerous (benign). Malignant brain tumors are cancers that typically grow faster than benign tumors, and quickly invade surrounding tissue. When benign or malignant tumors grow, they can cause the pressure inside the skull to increase. This can be the reason of brain damage, which is life-threatening. Brain tumors substantially affectquality of life and change everything for a patient and their loved ones. The American Cancer Society's estimated for 2021 that about 18,600 people (10,500 males and 8,100 females) will die from brain and spinal cord tumors in

The associate editor coordinating the review of this manuscript and approving it for publication was Amin Zehtabian.



(a) Axial (b) Coronal (c) Sagittal

FIGURE 1. MRI study scans [2].

the USA [1]. Magnetic resonance imaging (MRI) is the most popular technique for diagnosing brain tumor. MRI presents tremendous detail of brain, spinal cord, and vascular anatomy. These three visualized anatomy will have all three orientations: axial, sagittal, and coronal. The most popular MRI sequences are T1-weighted, T2-weighted scans, and Flair (Fluid Attenuated Inversion Recovery). The T1 weighted brain image also can be taken in 3D visualization of anatomy in all three planes:

Axial, coronal and sagittal as in Fig. 1. The axial orientation of the MRI head image is considered from neck to head. The coronal orientation starts on the tip of the nose and ends behind the head. The sagittal orientation extends from ear to ear.

Medical imaging modalities which include computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and positron emission tomography are non-destructive [2]. They consequently help in capturing the images of internal parts of organs [3], [4]. In the Content Based Image Retrieval (CBIR) domain for brain image, there are two major concepts in research works. One kind of method focuses on automatic retrieving images from Picture Archive and Communication System (PACS) like databases, which search images of the same imaging modality, body orientation, body region [5]. Another kind of method put their efforts into retrieving images that characterize the similar disease convenient for diagnostic comparing [6]–[8]. Manual MRI retrieval from a massive archive of imaging data with similar structures is a difficult and challenging task for radiologists. It relies upon the availability and understanding of the radiologist, who examines MR images and retrieves the relevant images from the archived data. This manual retrieval technique is impractical, non-reproducible, and time-consuming for a massive quantity of archived data.

To address this problem, automated CBIR is a probable solution for indexing archived images with minimal intervention through radiologists. In this research, we focus on CBIR for the retrieval of brain tumors images. Especially, while the radiologist provides a query image, the CBIR system retrieves the same pathological kind of brain tumor images from the database, then, the radiologist selects the maximum closely associated retrieved images and useful for diagnosis and treatment of the current case [9]. There are more than 120 forms of brain tumors that have been diagnosed by the World Health Organization (WHO) consisting of astrocytoma, gliomas, meningioma, medulloblastoma, pituitary tumors, and so on. These tumors are classified based on their location, grade, and nature of tumor cells. The clinical community specializes in glioma because the adults are focused on the same. Treatment of glioma relies upon its location, shape, and size [10].

In this research, we have designed a content-based system for retrieving Glioma brain tumor from MR images. Content-based image retrieval system uses the information presented in input image data and creates visual attributes of its content. In this proposed system we involve several filtering methods like Mean Filter, Median Filter, Conservative Filter and Crimmins Speckle Removal for removing noise and we adopt Gabor Walsh-Hadamard Transform strategy for feature extraction. Finally, we use Fuzzy C means with Minkowski to measure similarity distance for efficiently identify brain tumor using the obtained features. The proposed method is evaluated on a publicly available CE-MRI dataset, whole brain atlas dataset, IBSR web service and so on. We performed extensive experimental works for glioma brain tumor image retrieval from MRI and also test robustness, evaluated the performance of the proposed method, and compared our results with state-of-the-art brain tumor retrieval on the same dataset. The main contributions in this work are:

1. To retrieve the exact matching image from the dataset, implement noise removal using Mean Filter, Median Filter, Conservative Filter, and Scimmins Speckle Removal.

2. We adopt Hybrid of Gabor and Walsh-Hadamard Transform or feature extraction.

3. The proposed work is implemented on CE-MRI dataset, and IBSR dataset for content-based brain tumor retrieval using Fuzzy Clustering with Minkowski Distance.

The rest of the paper is organized as follows. Section 2 discusses the related work, Section 3 discusses proposed research framework and methodology in detail. Section 4 contains feature matching process. The experimental settings, retrieval performance, results and comparisons are shown in Section 5. And the conclusion is presented in Section 6.

II. RELATED WORK

The application of computer vision technique is Content-Based Image Retrieval (CBIR) system which retrieves images from large databases. CBIR is also known as Query by Image Content (QBIC). Retrieval of similar images from the large datasets based on extracting some features of color, texture and shape and enable indexing the images automatically [11]. Content-based image retrieval [12] has proposed a region of interest (ROI) for retrieving strategy. ROI is used as query input, then retrieves the tumor images from large dataset by using SIFT features. Local Binary Patterns (LBPs) were successfully used in Image CLEF med, 2D Hela, for texture feature extraction of brain MRI and it is retrieval tasks are implemented [13]–[15].

In medical image retrieval, global features such as global GIST, global HOG, global color histogram [16]–[18], and moments were also used in medical image retrieval [19]–[21].

Content-based brain tumor retrieval on the T1-weighted contrast-enhanced MRI (CE-MRI) dataset [22]–[24] proposed a margin information descriptor (MID) as a feature extractor. They use tumor region for querying the database to retrieval the same. Apart from traditional features such as shape, intensity etc., in this research they use margin information descriptor (MID). MID helps to define the tissues surrounding the tumor for describing the image content. Maximum mean average precision projection is used to find approximate value to improve retrieval performance.

By using region-based technique in the extraction of shape feature from Computer Tomography (CT) images are done using CBIR concept. Similarly, for classifying and retrieving the different medical images in CBIR using Support Vector machine (SVM) technique with different distance metric measures were used for analysis the result in terms of recall and precision [25]. In Deep Belief Convolutional Neural Network (DBCNN) concept CBIR system is used for retrieval of medical images. For pre-processing median filter is used [26]. In the pre-processing stage, Gradient vector field model and Median filter techniques are used for boundary detection. For designing CBIR in medical images Steerable filter is used for extracting feature of texture and for representing features of texture by using PCA technique. For retrieving the similar images from the large data set using Euclidean distance is described in article [27]. The segmentation of tumor tissues in the MRI Brain image using FCM and K-means clustering is performed. In the performance analysis K-means clustering performed better result [28]. To segment the Glioma tumor image, for the training process cascaded CNN architecture was implemented using patches [29]. To identifying the brain tumor Convolution encoder network (CEN), CNN, long short-term memory (LSTM), dual-force CNN and U-Net CNN were implemented [30]–[34].

Few surveys of important existing techniques are described in Table. 1.

The cells in abnormal condition react to form uncontrolled cell division in the brain is called cerebral tumor [39]. It replicates and destroys healthy cells in the human body. Grade 1 and grade 2 are low grade tumors. Grade 3 and grade 4 are high grade tumors. In this research, they classify normal and abnormal tumor brain from the MRI database. They use various wavelet transforms and support vector machines for accurate classification. The CNN with multi-modal information fusion [40] is used to obtain lesions of the brain under 3-D space. Compared to 2-D techniques, this method uses less fault input for processing. Though it is advanced, computational complexity in detection is high in this technique.

The multi-level features extraction [41] and concatenation for detecting brain tumor at the earliest is discussed. Two deep learning methods such as Inception-v3 and DensNet201 are used in efficient feature extraction process. Finally, outputs are concatenated and passed to the softmax layer for accurate classification. The main problem is more tough technology

TABLE 1. Survey of existing techniques.

Author	Data Set	Pre Processing	Feature Extraction	Feature Classification	Outcomes
Das et al. [35], 2019	HRCT, NEMA MRI Data Set	Gray Scale conversion	Krawtchouk Moments and HOG	Not mentioned	ARP=75.83% ARR=89.93%
Patil et al. [25],2019	Computed tomography images	Not mentioned	Region based Shape Feature extraction (Hu's Seven Moments)	SVM	Precision=55.19% Recall= 55.49%
Erfankhan et al. [36], (2017)	IRMA	Normalization and Resizing	Gabor Filter	SVM	Error Score=248.03
Liu et al. [37],2016	IRMA	resizing	Region of interest matching	CNN, Random Bar Code	Error Score=224.13
Sharma et al. [38], (2016)	IRMA	Not mentioned	Stacked Auto Encoders	Not mentioned	Retrieval error Rate = 21.76 Compression=74.61%

is implemented and the cost is high. Genetic algorithm [42] is used to detect an optimized edge in medical dataset. The algorithm called optimal threshold value is used for finite edge detection based on minimized cost. Feature of an input image is improved by using Balance Contrast Enhancement Technique (BCET) for providing better medical images with fine characters. In this, BCET cannot provide all features in superior quality. This technique is only useful for edge detection strategy. Edge detection cannot provide an accurate classification of all brain tumors.

III. PROPOSED METHODOLOGY

This study introduces a content-based image retrieval system for automatically identifying brain tumor from a large MRI images dataset. In this proposed work, we design a new framework for texture feature extraction by using a hybrid of Gabor Walsh-Hadamard Transform (GWHT). To retrieve similar brain tumor images for the input query image from the database, the distance metric measure is used for matching. To measure the distance for the similarity between query image and database images, we propose a distance metric of Fuzzy Clustering with Minkowski distance that has been newly introduced in this study. The optimization of the prediction system is designed into three phases such as.

Phase 1 (Pre-Processing): We remove noise from raw MRI dataset involving Mean Filter, Median Filter, Conservative Filter, and Scimmins Speckle Removal.

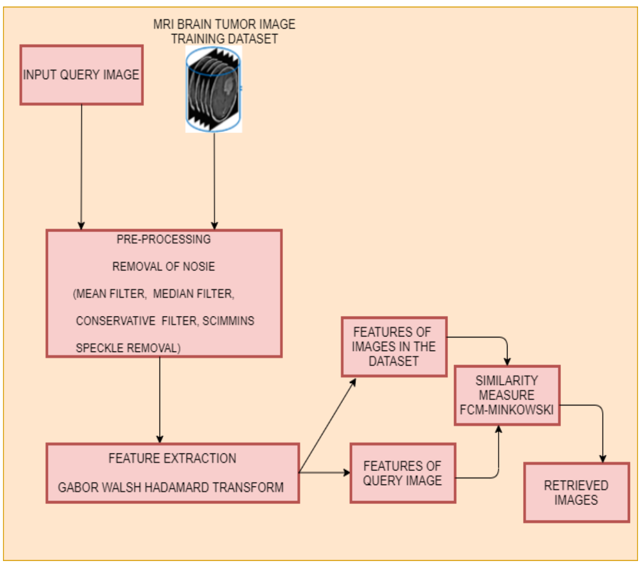


FIGURE 2. Proposed GWHT architecture.

Phase 2 (Feature Extraction): We extract significant characteristics of brain tumor exploring several feature extraction methods such as Gabor Transform, Wavelet Transform, Hough Transform, Hybrid of Gabor and Walsh-Hadamard Transform.

Phase 3 (Retrieval of Brain Glioma Tumor Image): We retrieve brain tumor images from MRI database using Fuzzy Clustering with Minkowski Distance. The architecture of the proposed system is shown in Fig. 2.

A. PRE-PROCESSING OF MRI IMAGES

The aim of pre-processing is to improve the high quality of the MRI brain images and make it in a form suited for further processing. In this work, we implemented image denoising to take away noise from brain image, which will restore the actual image [43]. For that purpose, we used Mean filter, Median filter, Conservative Filter, Crimmins Speckle Removal for producing effective results. Brain tumor images are very tough to preprocess using a single filter. Single filter output has more error features which makes the wrong prediction is existing research solution. Our multiple preprocessing step filters the noises accurately for further effectiveness. Each filter is described in detail in the following subsections.

1) MEAN FILTER

The mean filter is used to blur an image so that you can remove noise. It includes determining the mean of the pixel values in the form of a $M \times N$ kernel. The mean filter helps to reduce the variation of intensity between one pixel to next pixel. In this filter, the value of each pixel is replaced by the mean value calculated in a local neighborhood. Mean filter have the power to discard unrepresentative pixel values of their surroundings. The intensity value of the center pixel value is replaced by the mean value. Thus, it removes the noise in the image and we get smooth edges of the image. For a filter of length N, any filtered data point can be represented mathematically in terms of the average of the last N measured data points as

$$\hat{Y}_i = \frac{1}{N}\left(Y_i + Y_{i-1} + \cdots + Y_{i-1} + 1\right) \tag{1}$$

The mean filter can also be treated as a convolution of the measured signal with a vector of N constant coefficients, each equal {1/N}. For applying this filter in Python, by using Open-CV library to get a mean filter of the image. The resultant of applying mean filter is given below in Fig. 3.

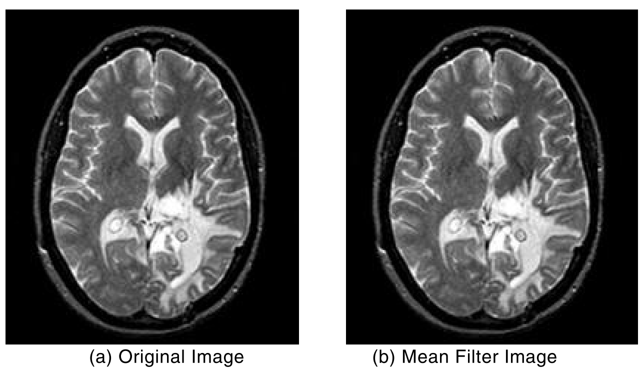


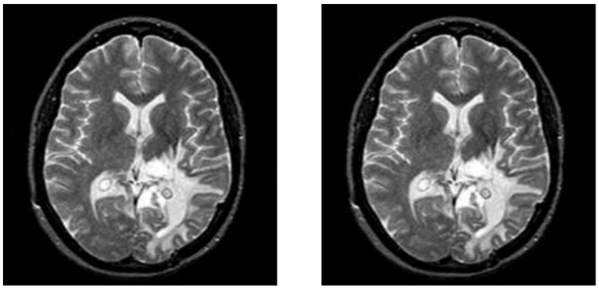
FIGURE 3. An example image of Mean Filter.

2) MEDIAN FILTER

The median filter, scan the entire image, using a 3×3 and recalculate the value of the center pixel by simply taking the median of all of the values inside the matrix, that is replaces it with the median of those values. Main advantage of using median filter is, it calculates robust average value than mean filter. Generally median value is any one of pixel value around neighbors. Therefore, it cannot create unrealistic value in pixel which help to preserve the sharp edges of images. This is very significant feature for brain tumor image.

$$\boldsymbol{X}\left[\boldsymbol{p},\boldsymbol{q}\right]=\boldsymbol{median}\left\{\boldsymbol{y}\left[\boldsymbol{i},\boldsymbol{j}\right],(\boldsymbol{i},\boldsymbol{j})\in\boldsymbol{Z}\right\}\tag{2}$$

where, Z represents a neighborhood pixel values defined by the user and the centered around location [p, q] in the image. The resultant of applying median filter is given below in Fig. 4.



(a) Original Image (b) Median Filter Image

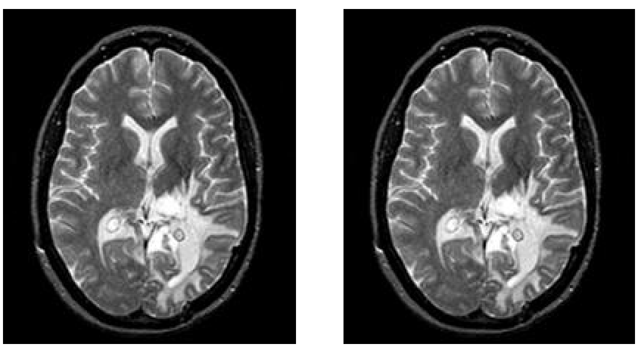
FIGURE 4. An example image of Median Filter.

3) CONSERVATIVE FILTER

smoothening the image and also reducing the noise in an image. It works by calculating the minimum and maximum neighboring values surrounding a grid cell value. If the intensity value of center pixel value is greater than the calculated maximum value, it is replaced with the maximum value in the output image. Let 4×4 window size of image. Take mid value of 4×4.

$$out_{img}=\left\{\begin{array}{ll} if\ mid > max; & max \\ if\ mid < min; & min \end{array}\right\}\tag{3}$$

Similarly, if it is less than the minimum value then it is replaced by the minimum value in the output image. The parameters which are used in conservative filter is neighborhood size, or filter size, is specified in the m and n dimensions. These dimensions should be odd, positive integer values (for example: 3, 5, 7, 9, etc.). Fig. 5 shows the resultant of applying the conservative filter.



(a) Original Image (b) Conservative Filter Image

FIGURE 5. An example image of Conservative Filter.

4) CRIMMINS SPECKLE REMOVAL

The Crimmins algorithm is used to remove speckle noise and smooth the edges. This algorithm compares the intensity of a pixel in an image with the intensities of its 8 neighbors. The algorithm considers 4 sets of neighbors (N-S, E-W, NW-SE, NE-SW). Let p, q, r be three consecutive pixels. Then the algorithm is:

For each iteration do the following steps.

a) Dark pixel adjustment: For each of the four directions

1) Process whole brain image with: if $p \geq q + 2$ then $q = q + 1$

2) Process whole brain image with: if $p > q$ and $q \leq r$ then $q = q + 1$

3) Process whole brain image with: if $r > q$ and $q \leq p$ then $q = q + 1$

4) Process whole brain image with: if $r \geq q + 2$ then $q = q + 1$

b) Light pixel adjustment: For each of the four directions

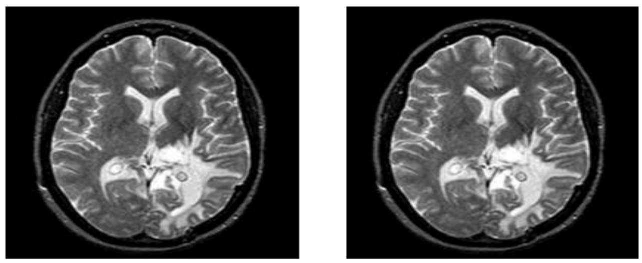
1) Process whole brain image with: if $p \leq q - 2$ then $q = q - 1$

2) Process whole brain image with: if $p < q$ and $q \geq r$ then $q = q - 1$

3) Process whole brain image with: if $r < q$ and $q \geq p$ then $q = q - 1$

4) Process whole brain image with: if $r \leq q - 2$ then $q = q - 1$

The resultant of Crimmins Speckle Removal is given in Fig. 6.



(a) Original Image (b) Crimmins Speckle Removal

FIGURE 6. An example image of Crimmins Speckle Removal.

B. FEATURE EXTRACTION

The main issue in CBIR is to extract the features which include texture, shape, etc. of the brain image efficiently and then represent them in a particular form to be used effectively in the matching of images. In our proposed work, we implement texture feature extraction by using hybrid of Gabor Walsh-Hadamard Transform (GWHT) technique. Gabor is a multi-scale, multi resolution filter [44]. In Gabor filter pixel value x and y denotes the position of the image. Here ω denotes center frequency, θ denotes the Gabor's orientation of direction and σ shows that standard deviation of Gaussian function with x, y axis of the image.

$$g\left(x,y,\sigma\right)=e^{-\frac{(x-x_0)^2}{2\sigma_x^2}-\frac{(y-y_0)^2}{2\sigma_y^2}}e^{j(\omega_{x0}x+\omega_{y0}y)}\tag{4}$$

where,

ω_{x0}, ω_{y0} - center frequency of x and y directions of the image.

σ_x, σ_y - standard deviation of the Gaussian function with x and y axis or direction.

x, y - Position of the image in pixel format.

Replace the Equation (3) as

$$\varphi(x, y, \omega, \sigma, \theta) = e^{-\frac{(x\cos\theta_k - y\sin\theta_k)^2}{2\sigma_x^2} + \frac{(-x\sin\theta_k - y\cos\theta_k)^2}{2\sigma_y^2}} \times e^{j(\omega_{x0}x\cos\theta_k + \omega_{y0}y\sin\theta_k)} \tag{5}$$

$$x\theta_k = x\cos(\theta_k) + y\sin(\theta_k) \tag{6}$$

$$y\theta_k = x\sin(\theta_k) + y\sin(\theta_k). \tag{7}$$

In this work, applied the orientation θ of Gabor direction as 0°, 20°, 40°, 60°, 120° with their frequency values of 60, 80, 120, 140. After applying the Gabor Transform to the brain image, the texture features are extracted, in this output applying the Walsh-Hadamard Transform (WHT) to get more accurate and efficient result. WHT is based on correlation between local pixels of the brain image. Walsh transform matrix can be defined as $WT_i, i = 0, 1, \ldots N-1$. The propoerties of WT are given below:

1. The values of Walsh Transform matrix is (WT_i) $+1$ and -1.
2. $WT_i[0] = 1\, forall\ i = 0, 1, \ldots N-1$
3. $WT_i \times WT_j^T = 0,\ for\ i \neq j.$
4. $WT_i \times WT_j^T = N\ for\ i = j.$

The Walsh transform matrix's row is equal to the row of Hadamard matrix and it is defined by index value of Walsh which is range from 0 to N-1. The Walsh transform matrix's row is equal to the row of Hadamard matrix and it is defined by index value of Walsh which is range from 0 to N-1. The properties of Hadamard matrix are given below:

1. $HD_n \cdot HD_n^{-1} = nId_n, Id_n -$ Identity Matrix and HD_n is the Hadamard matrix $\cdot$ (8)
2. $|HD_n| = HD^{1/2n}$ (9)
3. $HD_n \cdot HD_n^{-1} = HD_n^{-1}HD_n$ (10)

To change the order of Hadamard matrices by permuting rows and columns and also multiplying by the value -1 in rows and columns. The 4×4 matrix is defined as

$$HD_4 = \begin{bmatrix} HD_2 & HD_2 \\ HD_2 & -HD_2 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \tag{11}$$

Walsh Hadamard Transform (WHT) is defined by sparse factorization of Walsh transform matrix and each factor value is referred as stage. In the WHT the input and output value of each stage is defines as factor value of decomposition. The sparse factorization of identity matrix is obtained from HD matrix with its inverse function.

$$HDR^n = Ra^n \left(HDR^n\right)^{-1} \tag{12}$$

where

HDR^n - Walsh Hadamard Transform with radix R

Ra^n - Factorization of radix Ra

n - Number of input element

The WHT consists of Fourier and Cosine Transforms in the basic functions that are a set of orthogonal sinusoidal waveforms. The WHT applied in Squared size gallery space images generating M $\times$ M blocks from each image for texture feature extraction [41]. Here we are using 4 $\times$ 4 blocks. Instead of considering the whole pixels of the image selectively choose the super pixels by using clusteringmethod. These selected pixels are considered as kernel of M $\times$ M blocks. The texture features are extracted by projecting sum of selected kernels $\{k_0, k_1, k_2, k_3, \cdots k_{15}\}$ of WHT on theblocks of the image. The diagonal kernels are $\{k_0, k_5, k_{10}, k_{15}\}$ are selected for extracting the texture features of the image.

$$k_0 = \frac{1}{4}\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \tag{13}$$

$$k_5 = \frac{1}{4}\begin{bmatrix} 1 & 1 & -1 & -1 \\ 1 & 1 & -1 & -1 \\ -1 & -1 & 1 & 1 \\ -1 & -1 & 1 & 1 \end{bmatrix} \tag{14}$$

$$\kappa_{10} = \frac{1}{4}\begin{bmatrix} 1 & -1 & 1 & 1 \\ -1 & 1 & -1 & 1 \\ -1 & -1 & 1 & 1 \\ 1 & -1 & 1 & -1 \end{bmatrix} \tag{15}$$

$$k_{15} = \frac{1}{4}\begin{bmatrix} 1 & -1 & 1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & -1 & 1 & -1 \end{bmatrix} \tag{16}$$

To extract the texture feature and gives more clarity to the values by sum of the selected kernel values with projected onto the blocks of the image. These projection of selected kernel values for the blocks of the image is computed as following:

$$p_1 = \sum\nolimits_{i=1}^{m} b_i * k_0, \tag{17}$$

$$p_2 = \sum\nolimits_{i=1}^{m} b_i * k_5, \tag{18}$$

$$p_3 = \sum\nolimits_{i=1}^{m} b_i * k_{10}, \tag{19}$$

$$p_4 = \sum\nolimits_{i=1}^{m} b_i * k_{15}, \tag{20}$$

where b_i is the i^{th} block of the image.

p_1, p_2, p_3, p_4 are projection of selected kernels $\{k_0, k_5, k_{10}, k_{15}\}$ of the blocks of the image.

The sum of all projected kernels of the blocks image is calculated as follows:

$$s = p_1 + p_2 + p_3 + p_4 = \sum\nolimits_{i=1}^{m} b_i * k_s, \tag{21}$$

where s = 0, 5, 10, 15 are the diagonal kernel values of the image.

Algorithm 1 Gabor and Walsh-Hadamard Transform (GWHT)

Input: MRI brain tumor

Output: Texture Feature Extraction of tumor tissue of brain

1. Read the brain image as in binary form from the data set.
2. Applying the two-dimensional Gabor filter for the image by using Equation (4).
3. Select 16 × 16 image size of each block and applying the Fourier transform. Then select the Fourier transformed Gabor size of 8 × 8 of image having 5 orientations and 4 scale values.
4. Apply the Walsh-Hadamard transform, Partition each image into equal sized blocksof 4 × 4. $Im = \sum_{i=0}^{n} bl_i$ where n denotes the number of blocks.
5. Take the diagonal kernel values are $\{k_0, k_5, k_{10}, k_{15}\}$ for extracting the texture feature of the image.
6. Project the selected kernels of WHT on the blocks 4 × 4 of the image $s = \sum_{i=1}^{n} bl_i * k_s$. Where bl_i represents i^{th} block bl and k_n represents n^{th} kernel K and n denotes the number of blocks.
7. Calculate the texture strength of the image by using the formula $T = \left|bl_n^2 - k^2\right|$. The pixel intensity value of n^{th} block of bl image and the k represent the projected kernel values of n^{th} block of image.
8. Repeat the steps 6 & 7 for all blocks of the image calculate the texture strength of the image.
9. Each Blocks texture strength is taken as the super pixel $s_1, s_2, s_3, \cdots n$ of the image.
10. By using super pixels $s_1, s_2, s_3, \cdots, s_m$ of the image is consider as pixels and construct Gaussian adjacency matrix A and Diagonal Matrix D.
11. Construct Laplacian Matrix LMusing Gaussian adjacency matrix A and diagonalmatrix D.
12. To create unit matrix k by using denormalise the matrix LM.
13. For each row of unit matrix K; using K-means clustering, create a clusters. In which the value of pixels which is closest to the cluster centroid value.
14. Collect all pixel values in the K-clusters.
15. This collected pixel values are consider as tissues of brain tumor.

C. RETRIEVAL OF BRAIN GLIOMA TUMOR IMAGE FROM MRI DATABASE

In this work we used Fuzzy C-Means (FCM) algorithms with Minkowski distance to retrieve the similarity Glioma tumor images from the large image dataset [45]. Main objective of using this algorithm is, it minimizes the Euclidean distance between the data and cluster center. The FCM is stated by:

$$(U, X, \{A_i\}) = \sum_{i=1}^{k} \sum_{k=1}^{N} (\mu_{ik})^m D_{ik}^2 A_i, \tag{22}$$

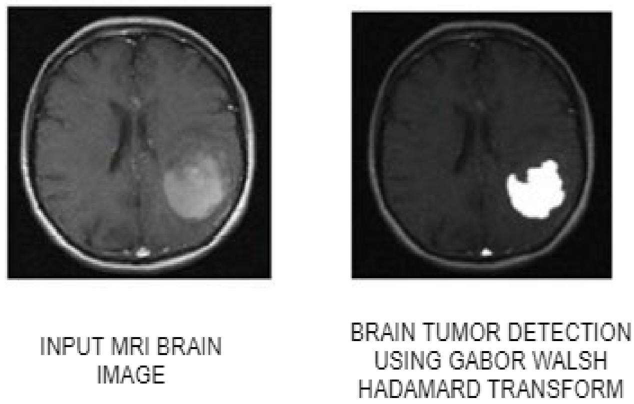


FIGURE 7. Result of proposed method (GWHT).

where, $U = \left[\mu_{i,j}\right]_{KXN} \in [0, 1]$

$$X = I^{n \times N}$$

where, U is partition matrix,

A_i is optimization variable used in local norm of matrix,

X is set of non-labelled data,

μ_{ij} *is the membership degree of data object* x_k *in cluster* k_i

$$\mu_{ij} = \frac{1}{\sum_{i=1}^{k} \frac{d_{ij}}{d_{il}}^{\frac{2}{m-l}}}, \quad i = 1, 2, \ldots, k;\ j = 1, 2, \ldots n \tag{23}$$

Minkowski distance is used.

$$\left(\sum_{i=1}^{n} |X_i - Y_i|^p\right)^{1/p}. \tag{24}$$

By using (22-24) Fuzzy C means with Minkowski distance. The most common method for comparing two images in content-based image retrieval is by using an image distance metric measure. For example, a distance of 0 signifies an exact match with the query. The retrieved images are ranked in ascending order based on their relevance.

IV. RESULT AND DISCUSSION

Dataset Description:For the experimental purpose 1500 MRI brain images are taken from MRI scan center and some images are from IBSR web service developed through CMA at Massachusetts General Hospital and the whole brain atlas [46]. Some images are collected from CE-MRI dataset. Almost all images are collected from 350 patients with a total number of 4500 images, but in this work, we proposed T1-weighted images with a default size of 256 × 256. We trained all images in the dataset by applying CBIR steps of pre-processing, feature extraction and feature matching process. And also repeat the same processing steps for the query image.

A. ANALYSIS FOR PREPROCESSING WORK

For removing noise and for smoothening images, we implemented Mean Filter, Median Filter, Conservative Filter, and Crimmins Speckle Removal using Python and investigated their effectiveness. Mean Filter and Median Filter resultshaveshowed bad filter performance for MRI image quality. The results of the Conservative filter are better filter compared to the mean filter and median filter. But smoothening of edges of the tumor image is not detect properly. So Crimmins Speckle Removal result gives better performance in terms of removal of noise and smoothening of the edges.

The peak signal-to-noise ratio (PSNR) is an engineering term defined as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is typically expressed in terms of the logarithmic decibel scale. It is most simply defined via the mean squared error (MSE) value for two m × n monochrome MRI brain images P and Q is defined as:

$$MSE = \frac{1}{MN}\sum_{I-0}^{M-1}\sum_{J-0}^{N-1}\left[P\left(i,j\right)-Q\left(i,j\right)\right]2 \quad (25)$$

Peak Signal-to-Noise Ratio (PSNR) value is defined as follows:

$$\mathrm{PSNR} = 20.\log_{10}\left(\frac{MAX}{\sqrt{MSE}}\right) \quad (26)$$

$$= 10.\log_{10}\left(\frac{MAX^2}{\sqrt{MSE}}\right) \quad (27)$$

where MAX is the maximum possible pixel value of the brain image. Here we used 255. In this work, we used average PSNR values as an indicator for evaluating the performance of different filtering methods. Tab. 2 shows average PSNR values of each tested filter of Mean Filter, Median Filter, Conservative Filter and Crimmins Speckle Removal Filter. The processing time, memory used for the mean filter and median filter was increase than conservative filter, Crimmins Speckle Removal. The efficiency of Conservative filter is bad in smoothening of the image. To compare all three filters, Crimmins Speckle Removal works better for removal of noise as well as smoothening of the image. Tab.2 tabulates average peak signal-to-noise ratio (PSNR) values of each tested filter.

TABLE 2. Average PSNR value for different types of filters.

Filter type	Avgerage PSNR value
Mean Filter	35.4601
Median Filter	46.6242
Conservative Filter	52.8245
Crimmins Speckle Removal	68.7679

From Tab.2, it is observed that our Crimmins Speckle Removal filter for removal of noise and smoothening of the image is better than other filtering techniques on the data set.

B. ANALYSIS RESULTS OF FEATURE EXTRACTION

This section discusses the experimental results of feature extraction carried out using Python. The results of the proposed GWHT feature extraction method are presented comparing the other existing three methods of Gabor Transform, Wavelet Transform, and Hough Transform are proposed in [47]–[50]. We used five metrics for analyzing the efficiency of the proposed method to detect the tumorous brain image. There are false alarm (FA), missed alarm (MA), sensitivity, specificity and accuracy. The classification error rate measured in terms of spurious detection of tumor images (FA) and fails to identify the tumor images (MA) are given in (28) and (29). The accuracy of the classification is measured by using the sensitivity, specificity, and accuracy are given from (30) to (32).

$$FA\ \% = \frac{FN}{Total\ Slices}\times 100 \quad (28)$$

$$MA\ \% = \frac{FP}{Total\ Slices}\times 100 \quad (29)$$

$$Sensitivity\ \% = \frac{TP}{TP+FN}\times 100 \quad (30)$$

$$Specificity\ \% = \frac{TN}{TP+FP}\times 100 \quad (31)$$

$$Accuracy\ \% = \frac{TP+TN}{TP+TN+FP+FN}\times 100 \quad (32)$$

where, true positive (TP) is number of tumor images correctly classified. True negative (TN) is number of normal images correctly identified. False positive (FP) is number of tumor image incorrectly classified as normal. False negative (FN) is number of normal image incorrectly classified as tumor images. Tab. 3 shows comparative analysis of proposed method.

The observed results from the Tab. 3 prove that the proposed method outperforms better than other existing approaches. The proposed method obtains 98% of accuracy on predicting the tumor images from the dataset. The resultant image is given in Fig. 8.

C. ANALYSIS RESULTS OF RETRIEVAL OF BRAIN IMAGE

This section presents the results of retrieval of brain image where precision and recall are used to measure for retrieval performance evaluation measures [22], [24].

$$Precision = \frac{No.of\ relevant\_images_{retrieved}}{Total\_No.of\ images\_retrieved} \quad (33)$$

$$Recall = \frac{No.of\ relevant\_images\_retrieved}{Total\_No.of\_relevant\_images\_retrieved} \quad (34)$$

Using this fuzzy c-means with Minkowski distance metric measure in (22), we can retrieve very closed similarity Glioma tumor images from the dataset.

Distance of 0 signifies an exact match with the query, and it is organized in rank order. Fig. 11 shows the result of retrieval of brain image from large data set by using fuzzy c-means with Minkowski distance metric measures. By applying these measures in (33) and (34). Fig. 11 shows the comparative performance of retrieval of the brain image.

The above Fig. 9 shows that the retrieved images are ranked in ascending order based on their relevance to the given input. The top 5 most similar retrieved images which is the precision at the position where 5 is the most similar database images

TABLE 3. Comparative analysis of proposed method (GWHT).

Feature Extraction Technique	FA%	MA%	Sensitivity %	Specificity %	Accuracy %
Gabor Transform	2.02	2.79	88.78	90.12	90
Wavelet Transform	3.04	3.67	65.9	68.34	69.11
Hough Transform	2.1	2.9	90.12	92.45	90.34
Our proposed method: Gabor Walsh-Hadamard Transform	1.02	1.05	96.77	98.40	97.93

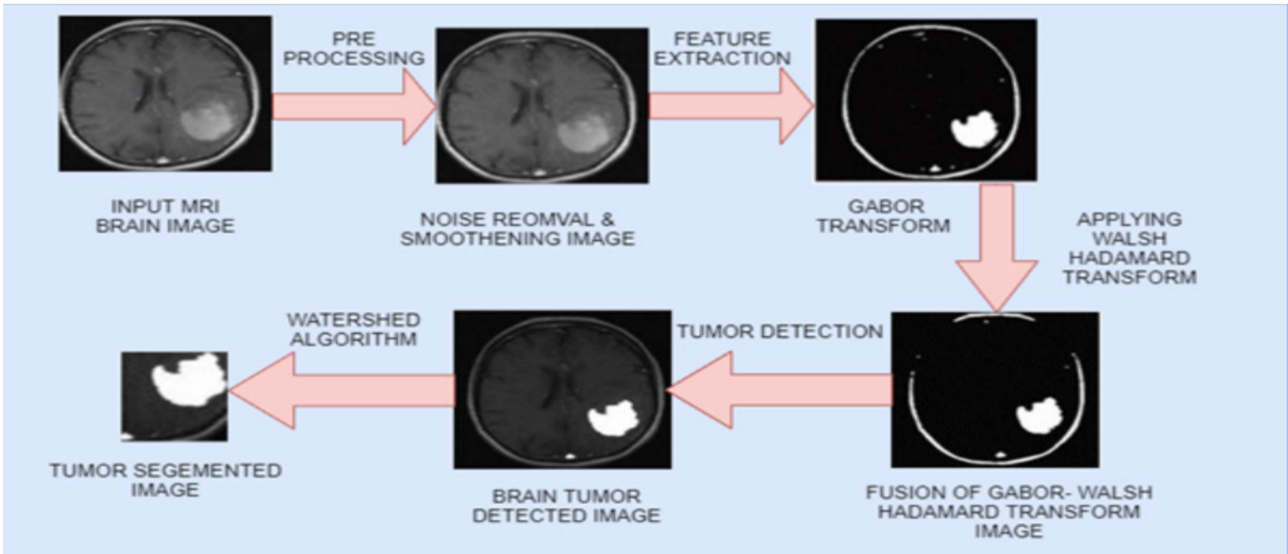


FIGURE 8. Feature extraction of proposed method.

FIGURE 9. Retrieval of brain image.

returned. Fig. 10 shows the comparitive performance measure using GWHT - Fuzzy C-Means with Minkowski distance methods and other existing techniques.

The evaluation results from Fig. 10, shows GWHT-fuzzy C-means with Minkowski Distance as a retrieval method that has good accuracy, good precision of 94.12%,

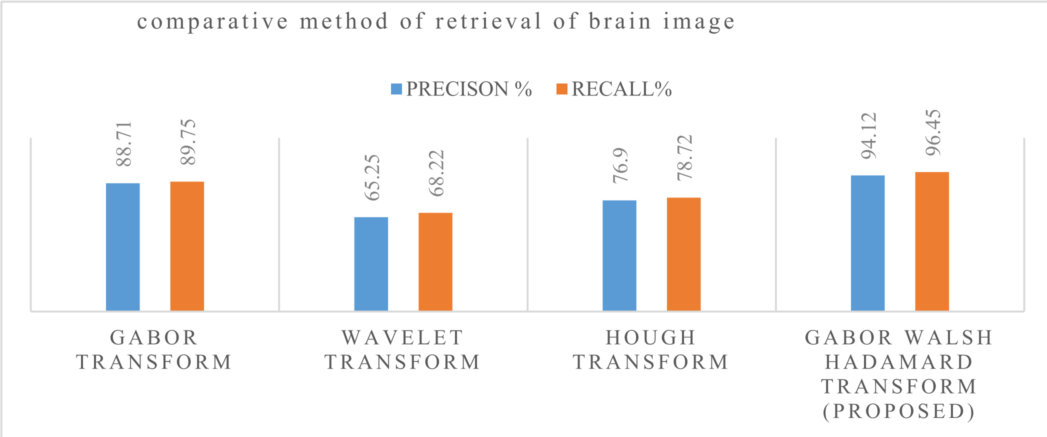


FIGURE 10. Comparative analysis of existing vs proposed methodology.

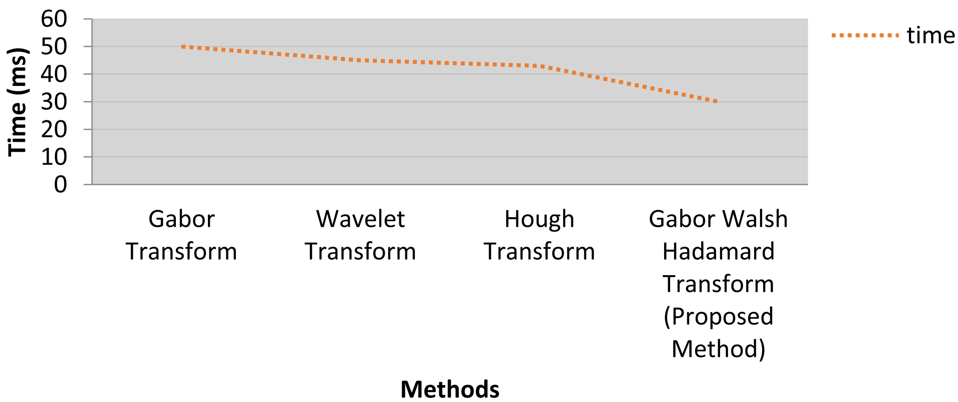


FIGURE 11. Time taken for image retrieval.

in retrieval of brain tumor images from the large database.

The experimental results show that this method can improve the results with an accuracy of around 94%. Fig. 11 shows time taken by all techniques and comparative study is performed. Our proposed takes only 30ms to compute the feature and identify the tumor features in the input-image.

Hence, our proposed algorithm, hybrid of Gabor Walsh-Hadamard Transform (GWHT) feature extraction and retrieval of images from the data set by using Fuzzy C means with Minkowski distance metric measures outperforms better in terms of accuracy, execution time, and efficient retrieval of images. This GWHT is more reliable and consume less time for extracting features. The super pixels are used to recover the tumor in an effective way and it proves better algorithm than any other existing algorithm. This will be the best method to predict the tumor patient efficiently and helpful to the medical industry for the diagnosis and early prediction of Glioma tumor patients.

V. CONCLUSION

Content-based image retrieval is challenging among recent image processing researchers. In this research article, we propose a new CBIR approach based on GWHT feature extraction technique for brain tumor retrieval. The proposed method yields better performance for retrieving the medical image with 97.9% of accuracy. Result evaluation shows our proposed technique is superior in precision and recall compared to other existing techniques. In addition, the proposed method took less time compared to other feature extraction methods. Retrieving nearest image helps radiologist to predict true positive results as early as possible. The limitation of the work is we cannot segregate false positive images in case of high similarity among the image pixels. Retrieving the relevant image based on features is considered as a first and foremost essential step for medical diagnosis. When this technique works with high accuracy, further processing techniques can predict diseases as early as possible. In future, this limitation can be achieved by some semantic-based similarity calculation techniques. Also for another limitation like high similarity of pixels of the image cannot be segregate as false positive; therefore, it can be solved by using optimization algorithm in Artificial intelligence or swarm intelligence.

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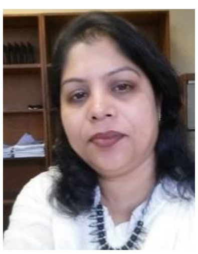
K. VENKATACHALAM received the bachelor's degree in information technology, in 2005, the master's degree in computer science and engineering, in 2008, and the Ph.D. degree in computer science and engineering, in 2018. He has more than 13 years of academic experience and currently working as Senior Research in the Department of Applied Cybernetics, Faculty of Science at University of Hradec Kralove, Hradec Kralove, Czech Republic. He has published several articles in peer-reviewed journals. His research interests include data mining, web services, semantic web services, distributed computing, and cloud computing. He is a Sun certified SCJP professional and has obtained Brain Bench certification in various disciplines. He has organized several workshops on J2ME, advanced java programming, web services, enterprise computing, web technology, and wireless sensor network (WSN) in his institution and has presented papers in web services at national and international conferences. He has guided a number of research-oriented and application-oriented projects organized by well-known companies, such as IBM. He has delivered more than 20 guest lectures in reputed engineering colleges on various topics.



SIULY SIULY received the Ph.D. degree in biomedical engineering from the University of Southern Queensland, Australia, in September 2012. She is currently a Research Fellow with the Institute for Sustainable Industries & Liveable Cities, Victoria University, Australia. She already made significant contributions to the mentioned areas that have been published in top leading journals and conferences. Her current research interests include biomedical signal processing, analysis, and classification, detection, and prediction of neurological abnormality from brain signal data (e.g., EEG data), brain–computer interface, machine learning, pattern recognition, artificial intelligence, and medical data mining. She is an Associate Editor of IEEE Transactions on Neural Systems and Rehabilitation Engineering (TNSRE) and a Managing Editor of *Health Informatics Sciences and Systems*. She is also an Associate Editor of *Frontiers in Medical Technology* and an Editorial Member of *Computers, Materials and Continua*, *Journal of Autonomous Intelligence*, *International Journal of Clinical and Medical Informatics*, and *International Epilepsy Journal*. Recently, she has authored a full book, titled *EEG Signal Analysis and Classification: Techniques and Applications* (Springer).

NEBOJSA BACANIN received the Ph.D. degree from the Faculty of Mathematics, University of Belgrade, in 2015, (study program computer science, average grade 10,00). He started his university career in Serbia 13 years ago with the Graduate School of Computer Science, Belgrade. He currently works as an Associate Professor and the Vice-Dean with the Faculty of Informatics and Computing, Singidunum University, Belgrade, Serbia. He has published more than 120 scientific papers in high quality journals and international conferences indexed in Clarivate Analytics *Journal Citation Reports* (JCR), *Scopus*, *Web of Science* (WoS), IEEEXplore, and other scientific databases, and in Springer Lecture Notes in *Computer Science* and *Procedia Computer Science* book chapters. He has also published two books in domains of *Cloud Computing* and *Advanced Java Spring Programming*. His research interest includes computer science and his specialty includes stochastic optimization algorithms, swarm intelligence, soft-computing and optimization and modeling, and artificial intelligence algorithms, swarm intelligence, machine learning, image processing, and cloud and distributed computing.

He is a member of numerous editorial boards, scientific, and advisory committees of international conferences and journals. He is a Regular Reviewer of international journals with high Clarivate Analytics and *Web of Science* (WoS) impact factor, such as *Journal of Ambient Intelligence and Humanized Computing*, *Soft Computing*, *Applied Soft Computing*, *Information Sciences*, *Journal of Cloud Computing*, IEEE Transactions on Computers, IEEE Review, Swarm and Evolutionary Computation, *Journal of King Saud University Computer and Information Sciences*, *SoftwareX*, *Neurocomputing*, *Operations Research Perspectives*, and so on. He actively participates in one national and one international projects from the domain of computer science. He has also been included in the prestigious Stanford University list with 2% best world researchers for the year 2020.

STEPAN HUBÁLOVSKÝ received the M.Sc. degree and Ph.D. degree from the Faculty of Mathematics and Physics, Charles University, Prague, Czech Republic, in 1995 and 1998, respectively. He became an Associate Professor with the Faculty of Informatics and Management, University of Hradec Králové, Czech Republic, in 2012, where he is currently the Vice-Dean with the Faculty of Science. His research interests include technical cybernetics, computer simulation and optimization, and big data processing.

PAVEL TROJOVSKÝ received the M.Sc. degree in teaching of mathematics, physics, and computer science from the University of Hradec Králové, Hradec Králové, Czech Republic, in 1989, and the Ph.D. degree in general questions of mathematics and computer science from the Faculty of Mathematics and Physics, Charles University, Prague, Czech Republic, in 2001. He became an Associate Professor in system engineering and informatics with the University of Pardubice, Pardubice, Czech Republic, in 2011. He is currently an Associate Professor and the Vice-Dean for Creative Activities with the Faculty of Science, University of Hradec Králové. His research interests include number theory and its applications in cryptography, applied mathematics, computer simulation and optimization, and big data processing.