

Efficient Sequential Pattern Matching Algorithm for Classified Brain Image

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Abstract

Objective: Medical Image Processing needs to have images to be processed in a more meaningful way for the diagnostic purposes. In the MRI diagnosis, the exact status of Brain tumor is not obtained. The objective of this research work is to find an MRI scanned image of brain is cancerous or not, because the benign stage is not visible so easily. **Methods:** In the research work, a novel approach is applied using Nearest Neighbour classification with Fuzzy Logic, directly accessing on the intensity of the pixels without omitting any region of the image. The Bayesian Classifier is further applied to classify the segmented regions such as normal and abnormal. The sequential matching is performed with every region using its feature space. It is also novel because it's using similarity measures of the trained set images and not on the geometric shape modeling. **Findings:** The MRI scanned image is applied with NN classifier using along with Fuzzy logic gives 12% to 18% is better than Multi region Graph cut. Contrast to existing NN classifier, the execution time in BCEV (Bayesian Classifier using Eigen Vector) is low and the variance is 10-20% low in the proposed BCEV. Compared with an existing and other works, the proposed efficient sequential pattern matching algorithm for classified brain image system provides an efficient estimation and the variance is 5-10% high in the proposed ESPM than when compared to BCEV, 8-10% higher than NN classifier and fuzzy logic method and 10-15% higher than existing graph cut method. **Application/Improvement:** The results show that our proposed approach gives high level of accuracy, execution faster and higher flexibility in segmentation, classification and in matching.

Keywords: Classification, Image Segmentation, Pattern Matching, Similarity Measure

1. Introduction

Numerous applications in image dealing out and computer vision involve identifying a distinct model in an image, pattern toning. To be practical in carry out, pattern matching techniques must be habitual, common, rapid and vigorous. Pattern matching is classically achieved by examining the whole image, and assessing a distance measure among the model and a confined rectangular window. The method proposed in this paper is pertinent to some outline shape, yet a non-contiguous one. We utilize the concept of "window" to envelop all probable shapes.

Over the years, pattern-matching has been regularly utilized in diverse computer requests, for instance, in editors, recovery of information (from text, image, or sound), and probing nucleotide or amino acid series patterns in sequence databases. The present day pattern-matching algorithms counterparts the model precisely or roughly inside the text. An accurate pattern-matching is to discover all the incidences of a scrupulous model ($x = x_1, x_2, \dots, x_m$) of m -characters in a classified image ($y = y_1 y_2 \dots y_n$) of n -characters which are constructed over a limited set of classified image indicated by α and the size of this set is identical to σ .

The shortest method is to evaluate the first m -char

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acters of the image and the model in some predefined classify and, after a match or a mismatch, decrease the complete pattern by one character in the onward route of the image. This process is repetitive until the prototype is situated at the $(nm+1)$ location of the image. This technique is normally recognized as a brute-force method. To assist this task, numerous algorithms have been planned, and these have their individual merits and demerits based on the prototype length, periodicity, and the kind of the image. Most of the eminent algorithms processed in two phases: i.e., the preprocessing stage and the seek phase. In the preprocessing stage, process the model and use this information in the seek phase to decrease the whole number of assessments and therefore decrease the general implementation time. The effectiveness of an algorithm largely depends on the seek stage.

Nearly all people who exercise computers appreciate and utilize pattern matching in several forms. Search engines on the Web employ outline matching to establish information of attention. Patterns can be precise or fairly common, employing diverse wildcards that counterpart numerous endings, words, or strings. Many databases contain an analogous ability, in which a concept can be comprehensive in numerous directions. Most bioinformatics databases include analogous pattern-matching abilities. Flexible prototype matching is called parallel searching. Similarity is a proportion series match among diverse sequences. The assumption is that similarity recounts to functionality, if two series are comparable, they will have associated functionalities. Only a similarity match creates intellect for probing between parallel functions. The prospect of a match presented by similarity searches surrenders a more practical amount for contrasting sequences than a precise match. There are numerous ways to attain the pattern matching employed in similarity searching.

In this work, an efficient sequential pattern matching algorithm is implemented to identify the feature space of the objects in the classified image where the objects are not fixed but are a random variable. A basic crisis in computer revelation, image segmentation has been the focus of a huge amount of hypothetical and sensible studies. Numerous studies have relied on discrepancy formulations since they effect in the most efficient algorithms. Very quick techniques have been devised in a separate manner. The most competent were those which exercise

graph cuts¹. In this structure, images are analyzed as distinct functions over a positional array.

Parallel matching among images has a set to supply to the image processing society. In ², proposed an easy image matching system supported on the location of the pixel values in the descriptions evaluated. When doing so we have restricted our work to images not containing a revolving discrepancy. Pattern toning is a significant job of the prototype detection process in today's world for eradicating the structural and efficient activities in a given image. Even though the pattern matching algorithm⁴ is normally utilized in computer science and information processing, it can be established in daily tasks. The approach in ³ used to evade redundant assessments in the DNA series. Owing to this, the number of assessments slowly reduces and assessment per character ratio of the planned algorithm decreases consequently contrasts to the some of the presented trendy methods.

The Devaki-Paul algorithm ⁵ for numerous pattern toning needs a pre-processing of the specified input text to organize a counter of the incidences of the 256 member ASCII character set. The piecewise constant data term representation⁶, and its Gaussian simplification, have been intensively utilized in the circumstance of unsupervised graph cut methods because user interference is not necessary and, particularly, the data term can be printed in the type necessary by the graph cut algorithm⁷. Nevertheless, though practical, these representations are not usually appropriate. For example, medical images are best explained by the Gamma allocation and Wishart distribution⁸. Level set partitioning⁹ is also being used for the pattern discovery process based on the patterns chosen. Region growing segmentation¹⁰ is also being used with the allocation of segmented image parts by adapting the medical images. But the segmentation process does not provide better user intervention outcome.

The mainstream of study in medical image segmentation pertains to its use for MR images, mainly in brain imaging¹¹. Instantly evaluation of different methods for segmenting MR images is also accessible¹². To enhance the medical image segmentation process, on this work, we present an efficient sequential pattern matching algorithm to identify the feature space of the objects in the classified image. Our previous work elaborately described the classification of medical image with the corresponding classifiers.

2. Methodology

The proposed work is efficiently designed for identifying the feature space of the object in the image. The proposed efficient sequential pattern matching algorithm for classified brain image system processed under three different phases. The first phase describes the process of formation of kernel for the medical images by performing the deviation of mapped image data within the scope of each region from the piecewise constant model and based on the regularization term based on the function of indices value of the region. The second phase describes the process of implementation of a Bayesian classifier-based Eigen vector model for classifying the image based on classes' presents. Before classification, the given image is segmented using nearest neighbor classifiers and fuzzy

logic which segments the image with high performance. The third phase describes the process of implementing the efficient sequential pattern matching algorithm based on similarity measures of dicom medical images. The architecture diagram of the proposed efficient sequential pattern matching algorithm for classified brain image system is shown in Figure 1.

2.1 NN Classifier and Fuzzy Logic for Image Segmentation

Let an image be represented as $M (m_1, m_2, m_3, \dots, m_K)$, where m denotes individual pixel within multi-dimensional data and K denotes the number of pixels. The method works through an optimization using graph cut procedure to The above figure describes the process

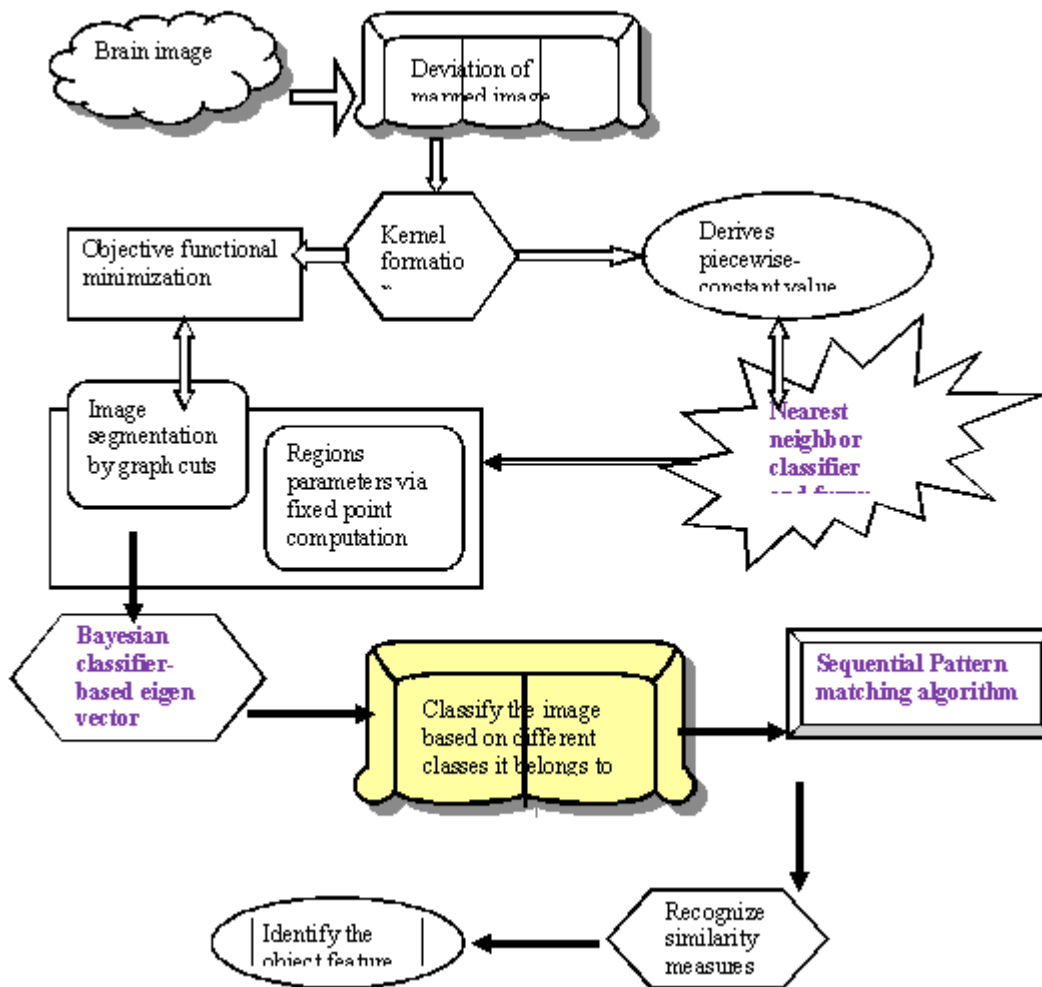


Figure 1. Architecture diagram of the proposed EPMACB.

of identifying the feature object space for a given medical image processing. At first, a medical image is given as input and identifies the deviation of mapped image data. After that, a kernel formation is used to identify the objective functional minimization and derived piece-wise constant value. Using graph-cut method, a given input medical image is segmented and processed. Then Bayesian classifier-based Eigen vector model is used to classify the segmented image based on its classes it belongs to. After classification, the proposed sequential pattern matching algorithm is used to identify the patterns present in the classified image. With the patterns, identify the similarity measures of the given pattern to identify the object feature space present in the given medical image reduce the functional objective which is defined as follows:

$$\mathcal{A} = \sum_{y=1}^K \sum_{x=1}^s \alpha_{xy}^c \|m_y - v_x\|^2, 1 \leq c < \infty \quad (1)$$

where α_{xy}^c represents the degree of membership of data elements m_y in the X^{th} segment, v_x is the centroid of the X^{th} segment, s is the number of segments to be partitioned, $\|m_y - v_x\|$ is a norm (distance measures are commonly applied) representing the distance which states the similarity between measured multi-feature data and the segment centroid, and c is a real constant greater than 1 which controls the resulting partition.

In nearest-neighbor classifier, each pixel is categorized in the similar class as the training data with the closest intensity with majority vote of the closest training data. The nearest-neighbor classifier is measured a nonparametric classifier since it makes no fundamental assumption about the statistical structure of the data. It assumes that the pixel intensities are independent samples from a mixture of probability distributions, usually Gaussian. This mixture, called a finite mixture model, is given by the probability density function.

$$F(q_j, \Theta, \pi) = \sum_{k=1}^K \pi_k F_k(y_j, \Theta_k) \quad (2)$$

Where q_j is the intensity of pixel j , F_k is a component probability density function parameterized by θ_k , and $\theta = [\theta_1, \theta_2, \dots, \theta_k]$. The variables π_k are mixing coefficients that weight the contribution of each density function and $\pi = [\pi_1, \pi_2, \dots, \pi_k]$. Training data is collected by obtaining representative samples from each component of the mixture model and then estimating each θ_k accordingly.

We evaluated the accuracy of segmentations via the Percentage of Misclassified Pixels (PMP) defined, in the two-region segmentation case, as

$$MP(\%) = \left(1 - \frac{|b_m \cap b_s| + |f_m \cap f_s|}{|b_m + f_m|}\right) * 100 \quad (3)$$

Where b_m and f_m denote the background and foreground of the ground truth (correct segmentation), b_s and f_s denote the background and foreground of the segmented image. Classification of new data is obtained by assigning each pixel to the class with the highest posterior probability. When the data truly follows a finite Gaussian mixture distribution, the ML classifier can perform well and is capable of providing a soft segmentation composed of the posterior probabilities. Finally, fuzzy logic is applied to the segmented images where each pixel is surrounded by eight nearby pixels.

2.2 Bayesian Classifier-based Eigen Vector Model for Classification for Segmented Image

Image classification is defined here as a crisis of handing over images to diverse classes consistent with the classes they contain. The Bayesian classifier permits formation of high-level classes that cannot be represented by individual pixels or regions. Besides, learning of these classifiers need only a few training images. The input to the system is a collection of training images that have instance images for each class defined by the user. Represent these classes by $w_1, w_2, \dots, w_s$. Calculate the number of times for every probable region group (combinatorial created using all probable relationships among all probable prototype regions) is established in the set of training images for all class. A region group of interest is the one that is regularly established in a scrupulous class but hardly ever exists in other classes. For each region group, this can be measured using class separability which can be designed in terms of inside class and between class variances of the counts as

$$\zeta = \log\left(1 + \frac{\sigma^2 B}{\sigma^2 W}\right) \quad (4)$$

Where $\sigma^2 W = \sum_{i=1}^s v_i \text{var}\{z_j \mid j \in w_i\}$ is the within

class variance

v_i is the amount of training images for class w_i ,

z_j is the counts of the region group found in training image j ,

$$\sigma^2 B = \text{var} \left\{ \sum_{j \in w_i} z_j \mid i = 1, 2, \dots, s \right\}$$

Is the between-class variance, and $\text{var} \{.\}$ denotes the variance of a sample.

Choose the top t region groups with the prevalent class separability values. Let $x_1, x_2, \dots, x_t$ be Bernoulli arbitrary variables for these section groups, where $x_j = T$ if the province group x_j is established in an image and $x_j = F$ or else. Let $p(x_j = T) = \theta_j$. Then, the counts of x_j is identified in images from class w_i has a allocation where v_{ij} is the number of teaching images for w_i that enclose x_j . The Bayes estimate for θ_j becomes

$$P(x_j = T \mid w_i) = v_{ij} + 1 / v_i + 2 \quad (5)$$

The Bayes estimation for an image fit in to class w_i (i.e. enclosing the object defined by class w_i) is calculated as

$$p(w_i) = \frac{v_i + 1}{\sum_{i=1}^s v_i + s} \quad (6)$$

For an unidentified image, investigate for each of the t region groups (determine whether $x_j = T$ or $x_j = F$) and consign that image to the finest identical class using the provisional independence assumption. With the regions being identified of each image pixels, Eigen vector is formed. Moreover, with the regions the eigen vector is formed by considering product of two square matrix 'P' with 'n' rows and 'n' columns with a vector 'v' results in another vector $w = 'Pv'$ is evaluated.

2.3 Sequential Pattern Matching Algorithm to Identify Feature Space

Once the classification of image using NN classifies and fuzzy logic is performed, now it is necessary to extract the features in the image. Using image segmentation results, the following features of segmented objects are extracted.

- Area: By determining the number of pixels in the segmented image parts consider I of the t -th frame, compute the area of the object $a_i(t)$.
- Width and height: Extract the positions of the pixel $P_{x_{\max}}, P_{x_{\min}}, P_{y_{\max}}, P_{y_{\min}}$ and determine the width $w_i(t)$ and $h_i(t)$ as follows,

$$w_i(t) = X_{\max,x} - X_{\min,x}, h_i(t) = Y_{\max,y} - Y_{\min,y}$$

- Positions: Identify the positions of each object ($X_i(t)$ and $Y_i(t)$) as

$$X_i(t) = \frac{X_{\max,x} + X_{\min,x}}{2}, Y_i(t) = \frac{Y_{\max,y} + Y_{\min,y}}{2}$$

- Color: Using image data $P_{x_{\max}}, P_{x_{\min}}, P_{y_{\max}}, P_{y_{\min}}$, define the color features of the object in the given medical image.

$$R_i(t) = [R(P_{x_{\max}}) + R(P_{x_{\min}}) + R(P_{y_{\max}}) + R(P_{y_{\min}})] / 4$$

The proposed pattern matching algorithm is done with image classification and feature extraction. For this, utilize a minimum distance search between (t, i) and all objects in the preceding frame $(t-1, j)$. The object (t, i) is identified with the object in the $(t-1)$ -th frame which has the minimum distance from (t, i) . By repeating the matching procedure in sequential manner that utilizes a decision matrix DM it is easy to track all the objects in the segmented image parts. $DM[p, n]$ represents the decision after sampling p non-identical features out of a total of n sampled features. The decision regarding the feature is of the two types namely I (identical) or NI (non-identical).

Next the framework evaluates the optimal decision matrix. In this way, the algorithm significantly identifies whether a pattern is identical or not. Moreover, the optimal decision matrix need not have to be computed for each new pattern. It is enough that it has to be computed once for a given prior on the distribution of the distances. Let us consider a scenario; if the task is to identify $20 * 20$ patterns, then it is highly significant if the decision matrix is computed once. Consider an object i in the t -th frame. Determine the distance among the neighboring objects (t, i) and $(t-1, j)$ as $D(t, i; t-1, j)$.

Consider an algorithm below described the sequential pattern matching based on minimum distance search in the feature space.

$P = 0$

Step 1: Extract the area, width, height, positions, and color data for segment i in the t -th frame

Step 2: Pattern matching is done using,

Step 3: Determine the calculation of distances,

Step 4: Search for the minimum distance,

Step 5: Identify the distance measure for feature object space tracking

Step 6: Identify the Euclidean distance,

Step 7: Estimate the positions of segment i in the next segmented parts

Step 8: repeat the matching procedures for all segments to identify the feature object space.

Step 9: For $n = 0$ to $|B|$ do

Step 10: if $DM[p, n] = NI$ then return non-identical

Step 11: if $DM[k, n] = I$ then return Identical

Step 12: sample uniformly and without replacement (a, b) m from B

Step 13: $p = p + \text{sim}(\text{pattern}, \text{window}, (a, b) m)$

With the above process, the pattern matching is performed efficiently with the Euclidean distance measure for feature objects in the segmented image parts. To start the sequential pattern matching, it is necessary to define the calculation of distance among the neighboring objects in the given image. The minimum distance is measured and identifies the distance measure of each object in the given image. With the Euclidean distance, the positions of segment i in the next segmented parts is identified. During each step, the algorithm samples corresponding features of each object in the given image goes right if they are found to be identical and goes wrong if they are found to be non-identical. In this example, $|B|$ is 20. With the patterns, similarity matching is also being done effectively based on the identification of nearing objects.

3. Experimental Setup

The performance of the proposed efficient pattern matching algorithm for classified brain image systems implemented in Math works Matlab 7.0. The intention of the proposed efficient pattern matching algorithm for

classified brain image system is to show how the feature space of the objects in the classified image are identified in which it belongs to using Bayesian classifier with no prior assumption regarding image model. The medical image (brain image) is taken as training set which is segmented into three regions. Segmented regions are based upon prior medical knowledge.

At first, the input medical image is segmented using nearest neighbor classifiers and fuzzy logic model. Then the Bayesian classifier-based Eigen vector model is used for the classification of segmented image based on its appropriate class for enhancing the image processing scheme. After classification, implement sequential pattern matching algorithm to identify the feature spaces of the object present based on its similarity measures. The purpose of this evaluation is to express the ability of the proposed efficient pattern matching algorithm for classified brain image system to adapt without human intervention to this class of images obtained with special techniques other than the common ones.

These results with gray level images demonstrate that the proposed efficient sequential pattern matching algorithm for classified brain image system that are robust and flexible with various types of images. The performance of the proposed efficient sequential pattern matching algorithm for classified brain image system is measured in terms of

- Estimation of object position
- Average matching accuracy
- Efficiency

Table 1. Segmented image parts vs. Estimation of object position

Segmented image parts	Estimation of object position (%)			
	Proposed ESPM	BCEV	NN classifier and fuzzy logic method	Existing graph-cut method
5	48	42	40	38
10	52	48	44	42
15	55	50	46	44
20	58	52	48	45
25	62	55	50	47

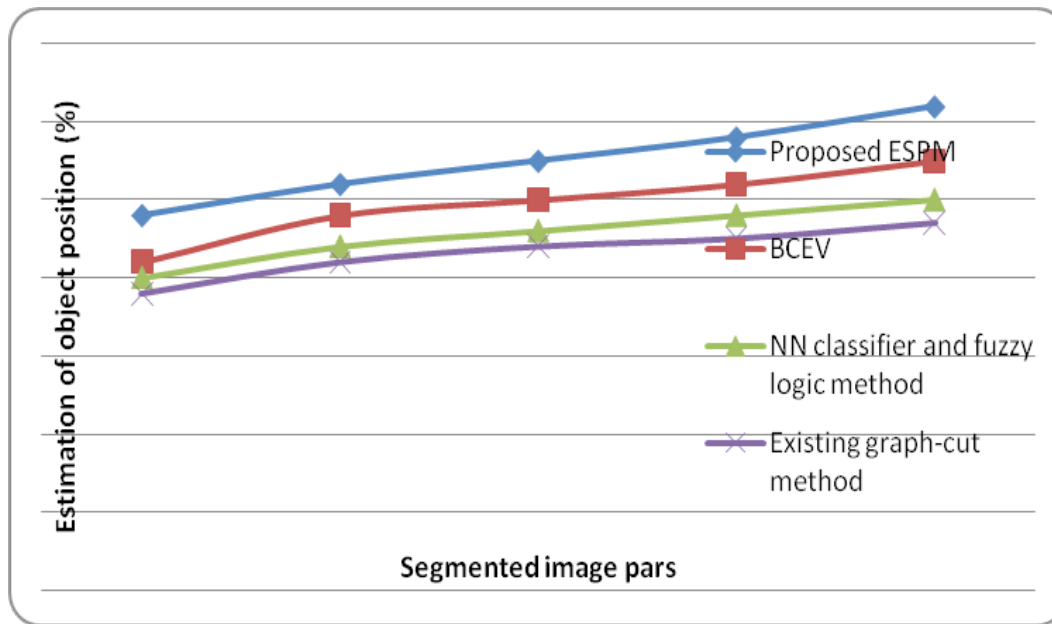


Figure 2. Segmented image parts vs. Estimation of object position.

4. Results and Discussion

In this work, we have seen that how the feature space of the object is efficiently identified with the proposed efficient pattern matching algorithm based on its classes in which it belongs to using pixel values. The experimental results evaluated in terms of number of images used, number of segmented portions. The below table and graph describes the performance of the proposed efficient sequential pattern matching algorithm for classified brain image system [ESPM].

Table 1 describes the accurate estimation of object position in the image segmented parts. The estimation of object position accuracy by the proposed efficient pattern matching algorithm for classified brain image system is compared with our previous works and an existing multi-region graph-cut method.

Figure 2 describes the estimation accuracy of object position in the image segmented parts. An identification of object at a particular position in a given image is a challenging task. To overcome the challenge, in this work, we proposed pattern matching algorithm to identify the object feature space on the segmented image by extracting the features at first. After that, based on the width and position of the object in the image, the minimum distance of the neighboring objects are identified and processed. With the distance measure, object in the image has been tracked efficiently in the proposed [ESPM]. But in our

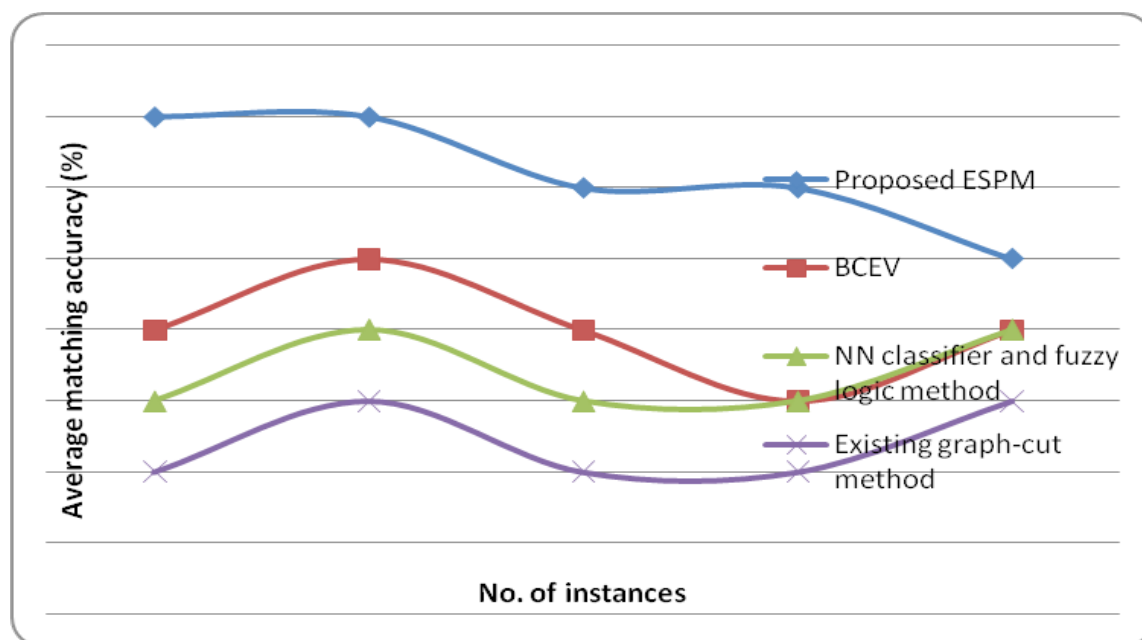
previous work, it simply concentrated on the classification of image with the features and does not help to identify the feature space. Existing multi-region graph cut method used generic model for all issues and provide the outcome with less efficiency. Compared with an existing and other works, the proposed efficient pattern matching algorithm for classified brain image system provides an accurate estimation and the variance is 5-10% high in the proposed ESPM than when compared to BCEV, 8-10% higher than NN classifier and fuzzy logic method.

Table 2 describes the average matching accuracy of the object positioned in the image segmented parts. The average matching accuracy by the proposed efficient sequential pattern matching algorithm for classified brain image system is compared with our previous works and an existing multi-region graph-cut method.

Figure 3 describes the average matching accuracy of the object positioned in the image segmented parts. We illustrate the average matching accuracy values on different kinds based on the number of training instances. The proposed ESPM method gets a large development on kinds with few training instances. This is significant since the allocation of objects in the genuine world is long-tailed. To enhance the process of matching algorithm, the pattern matching algorithm is used here. The sequential pattern matching algorithm started its matching process based on the distance measure of the objects in the given image. Moreover based on the similarity the features were

Table 2. Number of instances vs. average matching accuracy

No. of instances	Average matching accuracy			
	Proposed ESPM	BCEV	NN classifier and fuzzy logic method	Existing graph-cut method
2	0.7	0.4	0.3	0.2
4	0.7	0.5	0.4	0.3
6	0.6	0.4	0.3	0.2
8	0.6	0.3	0.3	0.2
10	0.5	0.4	0.4	0.3

**Figure 3.** Number of instances vs. average matching accuracy.

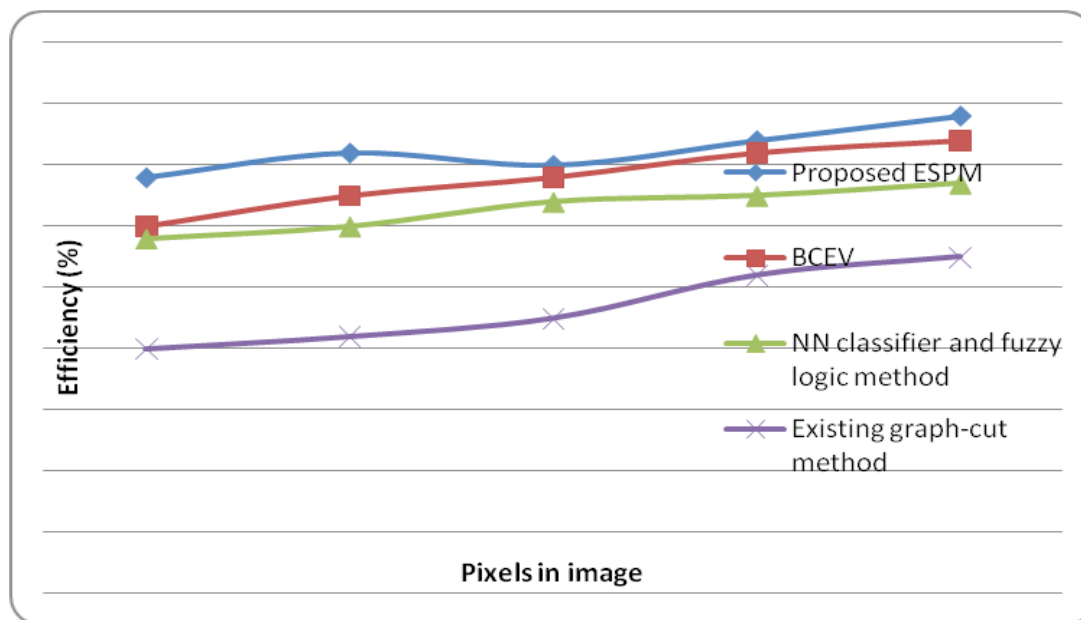
identified. Compared to the previous works simply concentrated on the classification of image with the features and does not help to identify the feature space. Existing multi-region graph cut method used generic model for all issues and provide the outcome with less efficiency. Compared with an existing and other works, the proposed efficient sequential pattern matching algorithm for classified brain image system provides an accurate estimation and the variance is 20-30% higher than BCEV, 30-40% higher than NN classifier and fuzzy logic method.

Table 3 describes the efficiency of the process of pattern matching algorithm in the image segmented parts. The outcome efficiency by the proposed sequential efficient pattern matching algorithm for classified brain image system is compared with our previous works and an existing multi-region graph-cut method.

Figure 4 describes the efficiency of the process of sequential pattern matching algorithm in the image segmented parts. The previous works simply concentrated on the classification of image with the features and does not help to identify the feature space. Existing multi-

Table 3. Pixels in image vs. Efficiency

Pixels in image	Efficiency			
	Proposed ESPM	BCEV	NN classifier and fuzzy logic method	Existing graph-cut method
100	68	60	58	40
200	72	65	60	42
300	70	68	64	45
400	74	72	65	52
500	78	74	67	55

**Figure 4.** Pixels in image vs. Efficiency.

region graph cut method used generic model for all issues and provide the outcome with less efficiency. Compared with an existing and other works, the proposed efficient sequential pattern matching algorithm for classified brain image system provides an efficient estimation and the variance is 5-10% high in the proposed ESPM than when compared to BCEV, 8-10% higher than NN classifier and fuzzy logic method and 10-15% higher than existing graph cut method. Finally, it is being observed that the proposed sequential pattern matching algorithm efficiently identified the feature space of the objects in the

classified image. The feature space of the image is easily identified with the patterns by extracting the features of the image.

5. Conclusion

In this paper, we have investigated sequential pattern matching algorithm to identify the feature spaces of the object present based on its similarity measures under medical images by achieving mapped image data deviation. Normally used geometric classifiers entail a group

of training data to efficiently compute the ethereal and textural signatures for pixels and also cannot do classification supported on high-level user concepts because of the deficient of spatial information. The proposal of our work gains the advantages of pattern matching scheme under similarity measures. An effectiveness of the proposed sequential pattern matching algorithm for segmented image classification method is evaluated using quantitative comparative performances over a large number of medical images especially brain images with the help of the optimal decision matrix to identify whether a pattern is identical or not. The performance evaluation is carried out by using quality metrics which show that compared to the existing multi-region graph-cut method; the proposed sequential pattern matching algorithm brings different advantages with regard to average matching accuracy attains 20-30% in classification process and flexibility attains 10-15% efficiency while analyzing the dicomm brain medical images.

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