Magnetic resonance imaging segmentation techniques using batch-type learning vector quantization algorithms

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Abstract

In this article, we propose batch-type learning vector quantization (LVQ) segmentation techniques for the magnetic resonance (MR) images. Magnetic resonance imaging (MRI) segmentation is an important technique to differentiate abnormal and normal tissues in MR image data. The proposed LVQ segmentation techniques are compared with the generalized Kohonen’s competitive learning (GKCL) methods, which were proposed by Lin et al. [Magn Reson Imaging 21 (2003) 863–870]. Three MRI data sets of real cases are used in this article. The first case is from a 2-year-old girl who was diagnosed with retinoblastoma in her left eye. The second case is from a 55-year-old woman who developed complete left side oculomotor palsy immediately after a motor vehicle accident. The third case is from an 84-year-old man who was diagnosed with Alzheimer disease (AD). Our comparisons are based on sensitivity of algorithm parameters, the quality of MRI segmentation with the contrast-to-noise ratio and the accuracy of the region of interest tissue. Overall, the segmentation results from batch-type LVQ algorithms present good accuracy and quality of the segmentation images, and also flexibility of algorithm parameters in all the comparison consequences. The results support that the proposed batch-type LVQ algorithms are better than the previous GKCL algorithms. Specifically, the proposed fuzzy-soft LVQ algorithm works well in segmenting AD MRI data set to accurately measure the hippocampus volume in AD MR images.

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1. Introduction

The image segmentation can be described as the image clusters whose points are associated to similar sets of intensity values [1]. Magnetic resonance imaging (MRI) segmentation provides important information for clinical diagnosis where different kinds of tissue and body fluids are associated to the clusters of similar image intensity values [2]. An efficient analysis of dual echo medical imaging volumes can be derived from a set of different diagnostic volumes carrying complementary information provided by medical imaging technology. The extraction of such volumes from imaging data is said to be segmentation, and it is usually performed in the image space by defining sets of pixels with similar features within a whole dual echo volume.

In general, medical images are obtained using different acquisition methods, including X-ray computer tomography (CT), single photon emission tomography, positron emission tomography, ultrasound, MRI, magnetic resonance angiographies (MRAs) and so on. Magnetic resonance (MR) imaging systems are important in medical image analysis. Magnetic resonance imaging has the multidimensional nature of data provided from either one of two different pulse sequences. Magnetic resonance imaging segmentation is an important step in any MRI image analysis. Various segmentation methods for MRI have been used to differentiate abnormal and normal tissues [3–9].

Quality of MRI is determined by the signal intensity and tissue contrast. Several factors such as the signal intensity, tissue contrast and image nonuniformity due to magnetic
field inhomogeneities are used to identify the quality of segmentation images in relation to real MRI images [10]. There are four measurements used to evaluate the MRI quality: (1) signal-to-noise ratio (SNR), (2) contrast-to-noise ratio (CNR), (3) region of interest (ROI) and (4) nonuniform gain tissue. Signal-to-noise ratio is a criterion for image quality. It is caused by electromagnetic noise in the body due to movement of charged particles and small anomalies in the measurement electronics, which depends on the size of the radio frequency (RF) coil and the bandwidth of the pulse sequence. We mention that large coils have a large measurement field but low SNR and vice versa. The closer the coil is to the object, the stronger the signal — the smaller the volume, the higher the SNR. Wider bandwidths decrease SNR.

Contrast-to-noise ratio is a summary of both SNR and contrast. It is the difference in SNR between two relevant tissues, types A and B, which is defined as CNR = \( \text{SNR}_A - \text{SNR}_B \). Good tissue contrast relies on optimal selection of appropriate pulse sequences (spin echo, inversion recovery, gradient echo, turbo sequences and slice profile). Important pulse parameters are repetition time (TR), time to echo (TE), time for inversion (TI) and flip angle. For T1-weighted images, it is important to select a good TR or TI. T2-weighted images depend on a good selection of TE. Tissues vary in their T1 and T2 times, which are manipulated in MRI by selection of TR, TI and TE, respectively. Flip angles mainly affect the strength of signal measures, but flip angles also affect the TR/TI/TE parameters. Resolution is a function of slice thickness, field of view (FOV) and matrix size. The in-plane resolution is a function of FOV/matrix size. Matrix size effects scan time, resolution and SNR. The measurement time is a function of the number of scans. Motion artifacts often result from involuntary movements (e.g., respiration, cardiac motion and blood flow, eye movements and swelling) and minor subject movements. Motion artifacts appear only in the phase-encoding direction and appear as ghosts or smears.

Magnetic resonance imaging exhibits nonuniform tissue intensities caused by inhomogeneities in the magnetic field, which lead to an artifact called a gain field [11]. Ozkan et al. [4] provided a neural network, which is a classification and segmentation technique that compensates for the problem of nonuniformity by estimating a gain field during the classification process. Guillemaud and Brady [12] compensate for the gain field effect by adding an additional tissue class to account for the nonuniform tissue. This method has shown to improve results. Quality of MRI also can be determined by comparing the volume of the ROI tissue. The closer the number of pixels selected in ROI of the segmentation image is to the number of pixels selected in the original MRI image, the better the accuracy is.

The Kohonen’s self-organizing map (SOM) is a competitive neural network that uses the neighborhood interaction set to approximate lateral neural interaction and discover the topological structure hidden in the data [13–15]. It is often used as an unsupervised clustering method with a sequential type of learning. These Kohonen’s sequential-type learning algorithms have proved to be extremely useful in detecting small lesions from smears. These techniques are equally useful in outlying the gain field (also called bias field) between tissues [16]. Recently, Lin et al. [17] proposed generalized Kohonen’s competitive learning (GKCL) algorithms. They successfully applied the GKCL algorithms in segmenting ophthalmologic MRIs and showed their efficiency and accuracy to outlying lesions. However, they also indicated that one must be careful when selecting learning rates, initials and parameters for these GKCL algorithms because these sequential-type methods are highly sensitive to those different selections. Theoretically, the batch-type schemes can decrease the number of interactions and also overcome sensitivity of algorithm parameters. On the other hand, MRI data sets are usually transferred from a selected MRI picture with fixed image size so that the batch types are supposed to be more suitable for these MRI data.

In this article, we consider the batch-type learning vector quantization (LVQ)-based segmentation techniques in segmenting MRI data. These batch-type LVQ segmentation techniques are compared with the GKCL methods proposed by Lin et al. [17]. The two actual MRI cases used in [17] are used for further comparisons based on sensitivity of algorithm parameters, the quality of MRI segmentation with the CNR evaluation and the accuracy of the ROI tissue. Overall, the batch-type LVQ segmentation results are better than the GKCL segmentation techniques. It is known that the fuzzy c-means (FCM) clustering is a fuzzy extension of k-means clustering. Each volume of the tissue fraction is the membership function to a particular class. The fuzzy membership functions from FCM algorithms give good interpretations of cluster memberships. Incorporating these fuzzy membership functions into LVQ learning shall become a good clustering algorithm. Based on the fuzzy-soft LVQ (FSLVQ) proposed by Wu and Yang [18], we present the FSLVQ segmentation technique. We find that FSLVQ can compensate for the problem of nonuniformity gain tissue and detecting small lesions from the image. Finally, a new case of MRI data sets where the patient was diagnosed to have Alzheimer disease (AD) is segmented with the FSLVQ segmentation technique. The resulting MRI segmentation impressively presents the algorithm efficiency with good segmentation results.

2. Materials and methods
2.1. Case summary

Three actual MRI data sets are used in this article. The first two cases are used in the comparisons of the batch-type LVQ algorithms to the GKCL algorithms proposed by Lin et al. [17]. The third case is specifically used for the proposed FSLVQ algorithm. To have quantitative measurements of MRI segmentation quality, we then present some
evaluation methods. These are described as follows. The first case is from a 2-year-old patient. She was diagnosed with retinoblastoma in her left eye, an inborn malignant neoplasm of the retina with frequent metastasis beyond the lacrimal cribrosa. The MR images, as shown in Fig. 1, showed an intramuscle cone tumor mass with high T1-weight image signals and low T2-weight image signals noted in the left eyeball. The tumor was measured to be 20 mm in diameter and occupied nearly the whole vitreous cavity. There was a shadysignal abnormality along the optic nerve to the level of the optic chiasm toward the brain. The MR images were obtained using a 1.5-T MR scanner with a multielement resonator head coil. Images were acquitted in the transsexual plane using a multisided interleaved two-dimensional (2-D) Fourier transform technique, with an FOV of 16×16 mm, slice thickness of 3.0 mm, gap of 5 mm and a 256×256-pixel matrix. That is, contiguous slices were acquitted. A standard spin-echo (SE) sequence with TR 300 ms and TE 13 ms was used to produce the MR images. A shadysignal abnormality was found along the optic nerve to the level of optic chiasm.

The second case of MRI data sets involves a 55-year-old woman, as shown in Figs. 4 and 5. She developed complete left side oculomotor palsy immediately after a motor vehicle accident. Her brain MRI with MRA, skull routine, orbital CT and cerebral angiography did not reveal a brainstem lesion, skull fracture or vascular anomaly. Her ptosis and eye adduction recovered partially 3 months later. According to clinical neurological signs, we hypothesized that the pathogenesis was the third nerve root avulsion with damage at the exit site from the midbrain caused by rotatory force. The MR images shown in Fig. 4 with MRA were obtained using 3-D FSPGR (three-dimensional fast spoiled gradient recalled acquisition in steady state), T2 with an FOV of 16×16 mm, slice thickness of 3.0 mm without gap and a 256×256-pixel matrix. Contiguous slices were acquitted. A standard gradient-echo pulse sequence with TR 9.9 ms and TE 4.2 ms was used to produce the MR image, as shown in Figs. 4 and 5. A shadysignal structural lesion abnormality in the oculomotor nerve was found at the exit site from the midbrain. The patient started to recover 3 months after the accident.

The third case involves an 84-year-old man who has had gradual onset of slowly progressive memory impairment since 1997. He was diagnosed to have questionable dementia (CDR=0.5) in 1999. His cognitive abilities screening instrument (CASI) was 71. He has had no history of stroke, but a brain CT in February 1999 showed lacunar infarcts in the bilateral external capsule and left lentiform nucleus, mild brain atrophy and mild periventricular low density. His cognitive function gradually deteriorated, and he was diagnosed to have AD in November 2000. His CDR was 1 and CASI was 78. However, he still has not experienced clinical stroke. The MR images, as shown in Figs. 9 and 10, were obtained using a 1.5-T MR scanner. TR 2650 ms with TE 82.23 was used to produce the MR images with slice thickness of 3.0 mm, gap of 5 mm and a 256×256-pixel matrix. In this case, the accuracy of the size of the hippocampal volume in the medial temporal lobe is our main concern.

2.2. Batch-type LVQ segmentation algorithms

Image segmentation involves partitioning image pixels into different cluster regions with similar intensity image values. Magnetic resonance imaging segmentation is an important technique to differentiate abnormal and normal tissues in MR images. Up to date, there are various neural network approaches proposed for the MRI segmentation. In these neural network-based approaches, Kohonen’s SOM is used most as the learning method in segmenting brain MRIs. The SOM is a competitive neural network that is often used as an unsupervised clustering method with a sequential type of learning. Recently, Lin et al. [17] successfully applied the GKCL algorithms in segmenting ophthalmologic MRIs. However, they indicated that one must be careful when selecting learning rates, initials and parameters for these GKCL algorithms, because these sequential-type methods are highly sensitive to those different parameter selections. To concern faster algorithms and overcome sensitivity of parameters, we propose batch-type LVQ segmentation algorithms. These batch-type algorithms should be more suitable for MRI segmentation because MRI data sets are usually transferred from a selected MRI picture with fixed image size.

The SOM proposed by Kohonen [13] is a two-layer feed-forward competitive learning neural network that can discover the topological structure hidden in the data and display it in one-dimensional or 2-D space. Suppose that \( v_k \) is the specified weight of the node \( k \) and the feature vector \( x_j \) is the input data at time \( t \), the winner neuron \( k \) among all competitive neurons is produced by the nearest neighbor condition as follows:

\[
||x_j - v_k(t - 1)|| = \min_i ||x_j - v_i(t - 1)||. \tag{1}
\]
The SOM uses then the following learning rule:
\[ v_i(t) = v_i(t - 1) + \alpha_i(t) h_{i,j,k}(x_j - v_i(t - 1)) \]  
(2)
where \( \alpha_i(t) \) is the learning rate of the node \( i \) and is confined to decrease monotonically with time \( t \). The neighborhood function \( h_{i,j,k} \) denotes the degree of excitation of the neuron \( i \). A simpler definition of \( h_{i,j,k} \) is
\[ h_{i,j,k} = \begin{cases} 1, & \text{if the node } i \text{ belongs to } N_k(t) \\ 0, & \text{otherwise.} \end{cases} \]  
(3)

\( N_k(t) \) is called the neighborhood set of the winner neuron \( k \) and is requested to decrease for accomplishing the winner-take-all (WTA) principle as time \( t \) increases. The learning vector quantization (LVQ) can be seen as a special case of SOM. In LVQ, the neighborhood set of each node will contain only the winner node with the WTA learning principle according the following simplest lateral interaction function:
\[ h_{i,j,k} = \begin{cases} 1, & \text{if } ||x_j - v_k(t - 1)|| = \min ||x_j - v_i(t - 1)|| \\ 0, & \text{otherwise.} \end{cases} \]  
(4)

In general, the WTA learning in LVQ is sequential, that is, the nodes are updated when each data is input in a sequential type. However, for a given and fixed feature vector set, a batch version of the SOM [15] can be considered so that it can be faster and does not require specification of any learning rate \( \alpha_i(t) \).

Assume that the convergence to a stationary state \( v^*_i \) with a sequential learning rule (Eq. (2)) is true. Thus, the expectation values of \( v_i(t) \) and \( v_i(t - 1) \) must be equal as \( t \) goes to infinity. That is, as \( t \to \infty \), for all \( i \)
\[ E[h_{i,j,k}(x_j - v^*_i)] = 0. \]  
(5)

Applying the empirical distribution to solve the above equation, we have
\[ v_i^* = \frac{\sum h_{i,j,k} x_j}{\sum h_{i,j,k}}. \]  
(6)

Because the calculation of \( h_{i,j,k} \) still depends on \( v_i^* \), the iterative method is used to approximate the explicit solution of \( v_i^* \). Thus, the batch LVQ can be summarized as follows (see Kohonen [15]):

**Batch LVQ algorithm.**

1. Fix \( c, T \) and give \( e \geq 0 > 0 \).
2. Initialize the weights \( v_i(0), i = 1, \ldots, c \).
   Input all feature vectors \( x_j, j = 1, \ldots, n \);
   Set the iteration counter \( t = 1 \).
3. For \( t = 1, 2, \ldots, T \):
   - Calculate all \( h_{i,j,k} \) at time \( t \) according to \( v_i(t - 1) \) using Eq. (4) and calculate \( v_i^*(t) \) using Eq. (6).
4. Compute \( E_i = ||v_i^*(t) - v_i^*(t - 1)|| = \sum_j ||v_i^*(t) - v_i^*(t - 1)|| \).
5. If \( E_i \leq e \), STOP; ELSE \( t = t + 1 \) and GOTO S3.

If we compare the previous LVQ with Kohonen’s competitive learning (KCL) proposed by Lin et al. [17], the main difference is that KCL is a sequential type and LVQ here is a batch type. The \( k \)-means (or called hard \( c \)-means) clustering is also a batch type for designing a vector quantizer, which is a mapping of input vectors to one of the \( c \) predetermined codebooks [19]. The FCM clustering is a fuzzy extension of hard \( c \)-means. The FCM and its varieties have been widely studied and applied in various areas [20–23]. Let \( X = \{ x_j, \ldots, x_n \} \) be a set of feature vectors. A partition of \( X \) into \( c \) clusters can be presented by the indicator functions \( \mu_{1}, \ldots, \mu_{c} \), such that \( \mu_i(x) = 1 \) if \( x \) is in \( X_i \) and \( \mu_i(x) = 0 \) if \( x \) is not in \( X_i \) for all \( i = 1, \ldots, c \). The fuzzy extension allows \( \mu_i(x) \) to be membership functions in fuzzy sets \( \mu_i \) on \( X \) assuming values in the interval \([0,1]\) such that \( \sum_{i=1}^{c} \mu_i(x) = 1 \) for all \( x \) in \( X \). For this case, \{\( \mu_1, \ldots, \mu_c \)\} is called a fuzzy \( c \)-partition of \( X \). The FCM objective function \( J_m \) is
\[ J_m = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m ||x_j - v_i||^2 \]
where \( \mu_1, \ldots, \mu_c \) is a fuzzy \( c \)-partition with \( \mu_{ij} = \mu_i(x_j) \), and \( m > 1 \) presents the degree of fuzziness. The FCM clustering algorithm is an iteration through the necessary conditions for minimizing \( J_m \) with the following update equations:
\[ v_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m} \]
(7)
and
\[ \mu_{ij} = \mu_i(x_j) = \left( \sum_{k=1}^{c} \frac{||x_j - v_k||^{2/m}}{||v_i - v_k||^{2/m}} \right)^{-1/m}, \quad i = 1, \ldots, c, \quad j = 1, \ldots, n. \]  
(8)

Based on the FCM update Eqs. (7) and (8), Bezdek et al. [24,25] proposed the so-called fuzzy LVQ (FLVQ). The neural lateral interaction function in FLVQ was defined as:
\[ h_{ij} = (\mu_{ij})^{-m} = \left( \sum_{k=1}^{c} \frac{||x_j - v_k||^{2/m}}{||v_i - v_k||^{2/m}} \right)^{-m} \]  
(9)
where
\[ m_i = m_0 + t \left( \frac{m_f - m_0}{\max NT} \right) \]  
(10)
and the prototype update equation is
\[ v_i = \frac{\sum_j \mu_{ij}^m x_j}{\sum_j \mu_{ij}^m} = \frac{\sum_j h_{ij} x_j}{\sum_j h_{ij}}. \]  
(11)

Bezdek and Pal [24] suggested that \( 1.1 < m_f \leq m_0 \leq 7 \). In the special case of \( m_0 = m_f = m \), FLVQ becomes the FCM clustering algorithm. If \( m_0 > m_f, m_i \) will descend to \( m_f \) as the iteration accomplishes the maximum number of iteration with the notation \( \max NI \). Since \( 0 \leq \mu_{ij} \leq 1 \), \( h_{ij} \) in FLVQ also follows \( 0 \leq h_{ij} \leq 1 \).
By descending the fuzzifier \( m_t \) of the FCM objective function to 1, the competitive learning in FLVQ will become WTA. Bezdek and Pal [24] noted that this competitive scheme can circumvent the problem of how to choose \( m \) for FCM. We can summarize the FLVQ algorithm as follows:

**FLVQ algorithm**

S1: Fix \( c, T \) and give \( \varepsilon \geq 0 \).

S2: Initialize the weights \( v_i(0), i = 1, \ldots, c \).

Specify \( m_0, m_f \) and maxNI.

Input all feature vectors \( x_j, j = 1, \ldots, n \).

Set the iteration counter \( t = 1 \).

S3: For \( t = 1, 2, \ldots, T \):

Calculate \( m_t \) using Eq. (10), calculate all \( h_{ij} \) at time \( t \) according to \( v(t-1) \) and \( m_t \), using Eq. (9), and calculate \( v(t) \) using Eq. (11).

S4: Compute \( E_t = ||v(t) - v(t-1)|| = \sum_{i=1}^{c} ||v_i(t)v_i(t-1)|| \).

S5: IF \( E_t \leq \varepsilon \), STOP; ELSE \( t = t+1 \) and GOTO S3.

The LVQ uses the WTA principle to approximate the neural lateral interaction as Eq. (4), which presents a crisp labeling for each node. Since the neighborhood set of the winner neuron \( k \) is negligible, the index \( k \) in \( h_{ij,k} \) will be omitted. Recently, Wu and Yang [18] used fuzzy functions to approximate \( h_{ij} \) with

\[
h_{ij} = \left( \frac{\mu_j(x)}{\max_{l \in C_k} \mu_l(x)} \right)^{(1 + \frac{\theta}{m_0})} \quad (12)
\]

where

\[
\mu_j = \mu_j(x) = \left( \sum_{k=1}^{c} \frac{||x_j - v_k||^{2}}{||x_j - v_k||^{2} - ||x_j - v_i||^{2}} \right)^{-1} \quad (13)
\]

are the well-known FCM membership functions. The learning rate is suggested as

\[
x_i(t + 1) = \frac{x_i(t)}{1 + x_i(t)h_{ij}} \quad (14)
\]

which is equivalent to the optimal learning rate in SOM [13–15]. The inhibition function \( f(t) \) is a positive strict monotone increasing function of \( t \), which is used to control the degree of inhibition within the neural lateral interaction. Since \( f(t) \) is confined as strictly increasing with \( \lim_{t \to \infty} f(t) = \infty \), this leads to the learning rule of this online FSLVQ tending toward WTA as \( t \to \infty \). Only the neuron that is the closest to the input data will be excited, and the other neurons will be inhibited. The function \( f(t) \) can determine the decreasing rate from fuzzy-soft competitive learning to crisp competitive learning (i.e., WTA). For example, using \( f(t) = t^2 \) will have a more strenuous inhibition (small excited states) than using \( f(t) = t \), and hence, the use of \( f(t) = t^2 \) will have a faster decreasing rate than the use of \( f(t) = t \). In general, \( f(t) = t^{1/2} \) is used.

Suppose that the sample size of the feature vectors is fixed, a batch version algorithm can help us to visualize the convergence state and speed up the learning. The batch version of FSLVQ, denoted by FSLVQ, can be constructed on the same construction of batch SOM assuming that above sequential algorithm will converge into a stationary state \( v^*_i \). The expectation values of \( v_i(t) \) and \( v_i(t-1) \) in FSLVQ must be equal as \( t \) goes to infinity. That is, as \( t \to \infty \)

\[
E[h_{ij}(x_j - v^*_i)] = 0 \quad (15)
\]

Applying the empirical distribution to solve the above equation, we have the batch learning formula of FSLVQ with

\[
v^*_i = \frac{\sum_j h_{ij}x_j}{\sum_j h_{ij}} \quad (16)
\]

where \( h_{ij} \) is as the definition on the Eq. (12), \( v^*_i \) is the weighted mean of all feature vectors whose weighted functions are the lateral interaction functions. We now summarize the FSLVQ algorithm as follows:

**FSLVQ algorithm**

S1: Fix \( c, T \) and give \( \varepsilon \geq 0 \).

S2: Initialize the weights \( v_i(0), i = 1, \ldots, c \).

Specify \( f(t) = t^{1/2} \) and \( m=2 \).

Input all feature vectors \( x_j, j = 1, \ldots, n \).

Set the iteration counter \( t = 1 \).

S3: For \( t = 1, 2, \ldots, T \):

Calculate \( \mu_j(0) \) and \( \mu_j(t-1) \) using Eq. (13), calculate all \( h_{ij} \) at time \( t \) according to \( \mu_j(t) \) using Eq. (12), and calculate \( v(t) \) using Eq. (16).

S4: Compute \( E_t = ||v(t) - v(t-1)|| = \sum_{i=1}^{c} ||v^*_i - v^*_i(t-1)|| \).

S5: IF \( E_t \leq \varepsilon \), STOP; ELSE \( t = t+1 \) and go to S3.

### 2.3. Evaluation measures

In order to have quantitative measures for evaluating MRI segmentation quality, we need to have some evaluation methods. In general, good quality MRI is determined by the signal intensity and tissue contrast. The image segmentation involves the partitioning of image gray scale pixels. Signal intensity is proportional to the pixel number [26] so that having a closer pixel count of the ROI tissue of segmentation as compared to the original MRI indicates good segmentation quality.

The SNR is a criterion for image quality, and the CNR is the difference in SNR between two relevant tissues, types A and B [10]. To measure SNR, we first record the histogram mean value of ROI tissue in the most homogeneous area of tissue (S) and then calculate the histogram S.D. for the largest possible area placed outside the object in the image background (N) [avoid ghosting (aliasing) or eye movement artifact regions]. The SNR is defined as mean signal (S) divided by S.D. of background noise (N), that is, \( S/N \). The difference between the CNR of relevant tissues with the batch-type LVQ algorithms and the original MRI
images represents the extent to which the batch-type LVQ algorithms improves the quality of the MRI image. The change in CNR can be written as follows:

$$\Delta CNR = CNR_L - CNR_O$$

where L is for LVQ segmentation and O is for original MRI image.

The CNR is calculated by subtracting the signal intensities (gray scale pixels) of the two tissues, types A and B, and then dividing the difference by the S.D. of the background noise (N). If we have that, L is for LVQ segmentation and O is for original MRI images. The two tissues are from the same MRI image so that the noise is the same. Hence, the formula can be written as follows:

$$\text{CNR}_O = \frac{S_O(A)}{N} - \frac{S_O(B)}{N}$$

$$\text{CNR}_L = \frac{S_L(A)}{N} - \frac{S_L(B)}{N}$$

$$\Delta \text{CNR}^*_N = \left( \frac{S_L(A)}{N} - \frac{S_L(B)}{N} \right) - \left( \frac{S_O(A)}{N} - \frac{S_O(B)}{N} \right)$$

where the tissue A is the ROI tissue and the tissue B is the tissue surrounding the ROI tissue. After the batch-type LVQ algorithms are applied to segment MRI images, the \(\Delta \text{CNR}^*_N\) is positive, which implies that the tissue contrast is better after the application of algorithms. Larger positive numbers for the \(\Delta \text{CNR}^*_N\) of the ROI tissue indicate good quality of the segmentation.

### 3. Results

In this section, we are concerned about the flexibility of algorithms, the quality of the MRI segmentation and the accuracy of ROI tissues. Lin et al. [17] had applied the GKCL algorithms to the segmentation of two ophthalmologic MRI cases. The results indicated that GKCL may be interfered with a biased set of starting learning rates even though these GKCL algorithms are robust to outlying lesions. Our proposed batch-type LVQ algorithms are quite flexible to starting learning rates. We will compare these LVQ algorithms with GKCL algorithms in this section. Reading the MRI image gray scale histogram in the first MRI case, there are five peaks that appeared in the 400×286-pixel (i.e., 114400) image. The gray scale range of MRI is 0 to 255. Larger gray scale numbers indicate brighter color. The brightest tissue was around 216. Lin et al. [17] used 5 sets of starting initials to test the efficiency and accuracy of the GKCL algorithms, where five clusters were recommended by an ophthalmologist. The categories are as follows: muscle tissue, connective tissue, nervous tissue, the lens and tumor tissue. The results indicated that the fuzzy-soft KCL (FSKCL) is more robust than KCL and fuzzy KCL (FKCL). But the segmentation quality is influenced by starting learning rates and parameter selection. The comparison results and analysis are described as follows.

#### 3.1. Flexibility and quality

For the purpose of comparing the flexibility of starting learning rates and also the quality of the MRI segmentation, two ophthalmologic MRI real cases with the same sets of starting initials used in Lin et al. [17] are applied to batch-type LVQ and GKCL algorithms.

##### 3.1.1. First case

The values of differences \(\Delta \text{CNR}^*_N\) of CNR between different segmentation methods and original MRI image for the first case are shown in Table 1. The gray scale pixel counts of the ROI for different segmentation methods are shown in Table 2. These counts are used to measure the accuracy of ROI and also to identify two categories of good quality (G) and unacceptable quality (U) from the segmentation methods as well as real MR images. The results of accuracy with G and U for different segmentation algorithms are shown in Table 3. Larger positive numbers of the \(\Delta \text{CNR}^*_N\) of the ROI tissue indicate good quality of the segmentation. We implement various algorithms, including LVQ, FLVQ, FSLVQ, KCL, FKCL and FSKCL, to observe the effects they have on CNR. This is done using the formula \(\Delta \text{CNR}^*_N\) described in Section 3. We obtain the mean gray scale pixel counts of the signal values directly from the original MRI images using Adobe Photo-

### Table 1

<table>
<thead>
<tr>
<th>Initials</th>
<th>LVQ</th>
<th>FLVQ</th>
<th>FSLVQ</th>
<th>KCL</th>
<th>FKCL</th>
<th>FSKCL</th>
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<tr>
<td>1</td>
<td>35.57</td>
<td>37.45</td>
<td>38.2</td>
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<td>38.16</td>
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<td>38.15</td>
<td>54.53</td>
<td>15.72</td>
<td>18.72</td>
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V: output values of MRI segmentation, O: histogram values of original MRI, \((S_{O(A)}-S_{O(B)})=177.11-162.83=14.28\).

### Table 2

<table>
<thead>
<tr>
<th>Accuracy of the ROI tissues</th>
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<td>LVQ</td>
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Histogram of ROI to original MRI=8 pixel numbers.

### Table 3

<table>
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<th>Quality of the segmentation image</th>
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<td>3</td>
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</table>

Accuracy with G, U for the MRI data set from the first case. G: good quality, U: unacceptable quality. Image size=400×286(114400), Max T=50, class=5, =0.01.
We first select the ROI tissue with the magic wand tool (tolerance=1, anti-aliased, contiguous) and use the histogram tool to obtain the signal intensity $S_{O(A)}$. Using the same method, we select the background tissue and measure its intensity $S_{O(B)}$. The difference of mean pixel counts in the ROI tissue ($S_{O(A)}=177.11$) and background tissue ($S_{O(B)}=162.83$) is calculated to find the $\Delta \text{CNR}*N=S_{O(A)}-S_{O(B)}=14.28$, where the value is also shown in Fig. 1.

Fig. 2. (A) Kohonen’s competitive learning segmentation result with good quality. $\Delta \text{CNR}*N=54.53$, ROI=54. (B) Kohonen’s competitive learning segmentation result with unacceptable quality. $\Delta \text{CNR}*N=0.74$, ROI=none. (C) Fuzzy KCL segmentation result with good quality. $\Delta \text{CNR}*N=12.12$, ROI=5. (D) Fuzzy KCL segmentation result with unacceptable quality. $\Delta \text{CNR}*N=16.02$, ROI=66. (E) Fuzzy-soft KCL segmentation result with good quality. $\Delta \text{CNR}*N=13.72$, ROI=5. (F) Fuzzy-soft KCL segmentation result with unacceptable quality. $\Delta \text{CNR}*N=3.02$, ROI=33.
Next, we illustrate how to calculate the \( \frac{S_{L(A)}}{C_0 S_{L(B)}} \) and \( \Delta \text{CNR}^*N \). We know that \( \Delta \text{CNR}^*N \) is the difference in CNR*N before and after each segmentation algorithm. Results from LVQ-based and KCL-based algorithms are calculated and recorded in Table 1. From Tables 1–3, there are five sets of initial values to implement various algorithms to test the flexibility of starting learning rates. The gray scale pixel count of abnormal tissue was around 216. Therefore, we use the set 4 to illustrate the \( \Delta \text{CNR}^*N \) calculation process listing in Table 1. The optimal set of the initial (84, 130, 160, 190, 216) indicated in the study of Lin et al. [17] is applied to different algorithms. The output results are (69.51, 100.70, 143.66, 193.51, 243.10). We obtain the mean gray scale pixel counts of the signal values directly from the segmentation images using Adobe Photoshop. The mean pixel count in the ROI tissue is around 193, and in the background tissue, around 143. Then we map the histogram to the output results. The mean pixel counts in the ROI tissue \( S_{L(A)} = 193.51 \) and background tissue \( S_{L(B)} = 143.66 \) are selected to find the \( \Delta \text{CNR}^*N \) where \( \frac{S_{L(A)}}{C_0 S_{L(B)}} = 49.85 \) and \( \Delta \text{CNR}^*N = 49.85 - 14.28 = 35.57 \), and the value of 35.57 is also shown in the set 4 vs. LVQ of Table 1. In Table 1, the other \( \Delta \text{CNR}^*N \) values of five sets of initials are presented for six segmentation algorithms. Learning vector quantization is consistently around 35, FLVQ at 37 and FSLVQ at 38. The results using KCL are higher than the LVQ methods at 54. However, the results are erratic. The image is very dark and hardly has any contrast or meaningful data. Fuzzy KCL and FSKCL are clearly less effective at increasing the SNR than the LVQ-based methods; the results are very inconsistent, ranging from 3 to 18. The results in Table 1 indicate that the proposed batch-type LVQ algorithms present more flexibility on starting learning rates and also better quality for the MRI segmentation than GKCL algorithms. Larger positive numbers of the \( \Delta \text{CNR}^*N \) of the ROI tissue indicate good quality.
quality of the segmentation. Moreover, the shapes of the abnormal tissue around the lesion area circled in the picture and shown in detail with the ΔCNR*N and ROI values are also shown in Figs. 2A to 3C.

3.1.2. Second case

To consider the segmentation efficiency, we use a window selection to the lesion area. In this way, we can accelerate the implementation speed of algorithms. We mentioned that the WTA algorithm can be effected by the pixels among each type of tissues in MRI. Therefore, this window selection can reduce the effect of this problem. The window selection from the second MRI data set shown in Fig. 4 is used to repeat the comparison procedures. According to the diagnosis from the neurological specialist and ophthalmologist, the pathogenesis is the nerve root avulsion and damage at the exit site from the midbrain. The lesion area on the nerve root is very small and mixed with edema-formed nonuniformity gain tissue. The window selection, as shown in Fig. 5, was suggested to enhance the small lesion under the recommendations of neurospecialists. The image was grouped into five tissue clusters: edema, gray matter, nerve tissue, white matter and cerebrospinal fluid. In this article, GKCL-based (KCL, FKCL, FSKCL) and LVQ-based (LVQ, FLVQ, FSLVQ) algorithms are used to analyze the same 203×209-pixel (42427) window selected MRI data set. The starting initial set (45, 85, 130, 171, 221) is selected according to the histogram set as the initial set 1. The mean gray scale of the oculomotor nerve is 45. Another set of staring initials (37, 60, 170, 187, 247) is assigned as the initial set 2, which is shown in Tables 4–6. We then implement GKCL-based and LVQ-based algorithms. The lesion area mean gray scales consist around 33. On the other hand, LVQ, KCL and FKCL only display the dark edema where the lesion area can hardly be seen. The image only shows the edema around the lesion area. We mentioned that the patient is gradually recovering after 3 months. The results from KCL-based algorithms do not match this situation. The LVQ-based FLVQ and FSLVQ algorithms actually provide the patient’s recovery information with flexible learning rates.

3.2. Accuracy and quality

The quality and accuracy of the ROI tissues is determined by the number of pixels selected when applying the magic wand tool (tolerance=1, anti-aliased, contiguous). The closer the number of pixels selected in the processed image is to the number of pixels in the original image, the better the accuracy. We demonstrate these considerations for the first and second cases as follows.

3.2.1. First case

The number of pixels selected in the original image was 8 pixels. When the LVQ, FLVQ and FSLVQ algorithms and F) give the good quality of oculomotor nerve abnormalities. It is clear that the damaged part of the oculomotor nerve is slightly connected. The results of LVQ (Fig. 7A and B) and GKCL-based (KCL, FKCL, FSKCL) (Fig. 6A to F) algorithms are erratic. The oculomotor nerve, circled in yellow, is very dark and hardly has any contrast or meaningful data.

In this MRI case, we select the damaged part of the oculomotor nerve as the ROI tissue. The same methods used in the first MRI case are applied to determine the quality of the image. For the original MRI, we calculate the difference in SNR of the ROI tissue (\(S_{O(1)} = 42.06\)) and background tissue (\(S_{O(0)} = 31.91\)) to find the CNR0, which is 10.15. The difference ΔCNR*N in before and after each algorithm is applied, calculated and recorded in Table 4. According to the ΔCNR*N values in Table 4, we find that FLVQ is consistently around 35, and FSLVQ is consistently around 34. However, the results of LVQ, KCL, FKCL and FSKCL are partially erratic. The result using FSKCL is lower than the LVQ-based methods at around 33. On the other hand, LVQ, KCL and FKCL only display the dark edema where the lesion area can hardly be seen. The image only shows the edema around the lesion area. We mentioned that the patient is gradually recovering after 3 months. The results from KCL-based algorithms do not match this situation. The LVQ-based FLVQ and FSLVQ algorithms actually provide the patient’s recovery information with flexible learning rates.

### Table 4

<table>
<thead>
<tr>
<th>Initials</th>
<th>LVQ</th>
<th>FLVQ</th>
<th>FSLVQ</th>
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<th>FKCL</th>
<th>FSKCL</th>
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<td>14</td>
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<td>8</td>
<td>16</td>
<td>12</td>
</tr>
<tr>
<td>37, 60, 170, 187, 247</td>
<td>None</td>
<td>13</td>
<td>17</td>
<td>None</td>
<td>None</td>
<td>5</td>
</tr>
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</table>

Histogram of ROI to original MRI=16 pixel numbers.
Fig. 6. (A) Segmentation result with unacceptable quality. (B) Segmentation result with unacceptable quality. (C) Segmentation result with unacceptable quality. (D) Segmentation result with unacceptable quality. (E) Segmentation result with good quality. (F) Segmentation result with unacceptable quality.

Fig. 7. (A) Learning vector quantization segmentation result with good quality. (B) Learning vector quantization segmentation result with unacceptable quality. (C) Fuzzy LVQ segmentation result with good quality. (D) Fuzzy LVQ segmentation result with good quality. (E) Fuzzy-soft LVQ segmentation result with good quality. (F) Fuzzy-soft LVQ segmentation result with good quality.
were applied, 5, 6 and 8 pixels were selected, respectively. These results are very close to the original value of 8, especially FSLVQ. When KCL, FKCL and FSKCL were applied, values ranging from 5 to 45 were obtained. These KCL-based results are much less accurate than those of the LVQ-based algorithms. These results are shown in Table 2 and also in Figs. 2A to 3C with the area circled in the picture.

3.2.2. Second case
The number of pixels selected in the original image was 16 pixels. When the KCL-based and LVQ-based algorithms were applied to the second case with the initial set 1, there are 11, 14, 17, 8, 16 and 12 pixels selected, respectively, as shown in Table 5. We find that the results from FLVQ, FSLVQ and FKCL are close to the original value of 16. However, only FSLVQ got a stable good result for the initial set 2. The other results of quality are shown in Table 6 and Figs. 6A to 7F where the area is circled in the picture. Overall, the LVQ-based algorithms have better results than the KCL-based algorithms, especially FSLVQ. However, the lesion area on the nerve root disappears in the edema and forms nonuniformity gain tissue from the segmentation results of both KCL-based and LVQ-based algorithms. Next, we shall discuss more about the nonuniform gain tissue stripping from ROI.

Guillemaud and Brady [12] took an iterative method correction for nonuniformity using an additional tissue class and improved the results. The LVQ-based algorithms are flexible in learning rates. However, the results from these LVQ-based algorithms in the initial set 2 failed to enhance the nerve root. We apply the method by adding one tissue class to strip the nerve root from the nonuniform gain tissue. An additional initial 43 is added to the initial set 2 of (37, 60, 170, 187, 247) and then applied to LVQ-based algorithms with the original MRI. The initial 43 is very close to the mean gray scales of the ocular motor nerve 45. The six outputs from the LVQ segmentation image are (8.62, 43.19, 89.64, 140.68, 193.82, 251.53). We use each output to draw pictures of skulls. The procedure involves changing all the pixels in LVQ-based segmentation image to 0 (black), except the pixel belonging to the selected output. The selected output will transfer to 255 (white). The picture using output 43.19, as shown in Fig. 8A, displays the part of the ocular motor nerve. We mark the ROI tissue with circle. The picture shows the nonuniformity gain tissue only as shown in Fig. 8A. Since the results in Tables 4 and 5 indicate that the FSLVQ is more robust than other LVQ-based and KCL-based algorithms, we repeated the same procedure to the FSLVQ algorithm. The initial set 1 of (45, 85, 130, 171, 221) with an additional initial 40 is used to calculated the results. The six outputs from the FSLVQ segmentation image are (15.05, 41.5, 46.96, 59.61, 116.34, 175.29). The picture using output 41.5, as shown in Fig. 8B, indicates that the delicate ocular motor nerve is lifted from the nonuniform gain tissue.

3.3. Mensuration of brain tissue volumes for the third case
Alzheimer disease and vascular dementia are the two most common diseases causing dementia. There is a change in hippocampal volume in brain MRI in individuals with mild cognitive impairment (MCI). Although these MCI individuals did not have stroke, nor neurological deficits,
about two thirds of them had at least one subcortical lacunar infarct. The proposed risk factors for converting MCI to AD include apolipoprotein E4, delayed recall, smaller hippocampal volume and decreased blood flow on brain HMPAO-SPECT, but there is no universal agreement. Therefore, the accuracy of calculating the hippocampal volume in the nemedial temporal lobe is a main concern to predict the conversion of MCI to AD. Many MRI data sets that contain the hippocampus are added together to calculate the hippocampal volume in the nemedial temporal lobe. Thus, the segmentation efficiency and accuracy are very important for the AD MRI data sets. Overall, the results from the previous two cases show that the images with the FSLVQ algorithm maintain accuracy, good quality of segmentation images and also flexibility of initials in all the comparison consequences. Therefore, we apply FSLVQ to the third MRI data set, which is shown in Fig. 9.

A window is carefully selected so that it can include the hippocampus and amygdala. There are four types of tissues included in the window-selected MRI shown in Fig. 10. These are the gray matter of hippocampus and amygdala, and the white matter of CSF and vessels. However, the hippocampus in Fig. 10 is surrounded by CSF, and the amygdala is located on top of the hippocampus. Both the hippocampus and amygdala are gray matters and separated with a thin layer of white matter. The most tedious procedure is to outline the hippocampus from the amygdala. However, the resolution of the sensors and the position of coils will put the noise in the image if the tissue is as thin as 0.01 mm. The noise of MRI images always presents overlapping gray scale intensity, which forms the nonuniformity gain tissue. Therefore, after consulting with the radiologist, there are two more clusters that need to be added to define the overlapping thin layers between the gray matters. One is nonuniformity tissue between the gray matters. The pixel range of ROI is around 53. The other is the nonuniformity tissue between CSF and the gray matter. The pixel range of ROI is around 66. That is, there are a total of six clusters in the MRI data set of Fig. 10. We use two sets of initials to the FSLVQ algorithm to test the flexibility and quality for this AD MRI case. One set of starting initials (41, 53, 66, 87, 100, 125) is selected according to the histogram, and another set of starting initials (37, 55, 85, 120, 131, 150) is randomly selected. Both starting initials approach the final outputs (31, 47, 61, 75, 97, 121) with different decimal numbers. The results indicate that the FSLVQ algorithm is flexible for initials. In this case, we emphasize the thin layer of white matter, the ROI tissue, between the hippocampus and amygdala. For the original MRI, we calculate the difference in SNR of the ROI tissue (\(S_{O(A)}=53.4\)) and background tissue (\(S_{O(B)}=62.5\)) to find the \(\Delta\text{CNR}^*N\) value, which is 9.1. The difference \(\Delta\text{CNR}^*N\) in before and after each algorithm is calculated. The mean pixel counts in the ROI tissue (\(S_{L(A)}=61\)) and background tissue (\(S_{L(B)}=75\)) is selected to find the \(\text{CNR}^*N\) value, which is \(\text{CNR}^*N=(S_{L(A)}−S_{L(B)})=14\) and \(\Delta\text{CNR}^*N=14–9.1\), that is equal to 4.9. The results shown in Fig. 10B display a good quality segmentation image. For the purpose of locating the nonuniformity gain tissue, the overlapping gray scale of gray matter and white matter, we manipulate the final image data set in Fig. 10B by changing the pixels with gray scale of 61 to gray scale 255 and other pixels to gray scale 0 and then display the single initial image in Fig. 10A. Compare the segmentation results in Fig. 10A with those in Fig. 10B, and the overlapping is displayed as a dashed line and pointed out by arrows. On the upper right of the image, two arrows point out the dashed line between the hippocampus and amygdala, and the arrows shown in the lower part of the image show the dashed line between CSF and gray matter. Therefore, the dashed lines provide an unbiased way to locate the ROI tissue and an accurate way to measure the volume of the tissue.

4. Discussion

In this article, we considered the batch-type LVQ segmentation techniques. These LVQ-based algorithms were compared with the GKCL-based algorithms based on the criteria of the algorithm flexibility of initials and the
segmentation accuracy and quality with the two real cases of MRI data sets used in Lin et al. [17]. Although they successfully applied the GKCL algorithms to MRI segmentation and concluded that FSKCL was most robust to outlying lesions, it is still easily interfered by a biased set of starting learning rates. We mentioned that MRI has its limitation to the size of the ROI tissue. It may be caused by the digital noise in the partial volume effects originating from the low resolution of the sensors. Thus, a window selection technique of MRI images can be used to clarify the image noise. It can provide good solutions and also speeds the algorithms. According to our comparison results for the window-selected MRI data sets, FSKCL and FSLVQ are both good for MRI segmentation. However, FSLVQ presents flexibility in initials, much accuracy and also better quality in most of the consequences than FSKCL. Therefore, FSLVQ is highly recommended for use in MRI segmentation as an aid for supportive diagnoses.

Finally, the FSLVQ segmentation algorithm was used to MRI segmentation for a new important case where a patient was diagnosed to have AD. It is known that MCI is a transitional state between normal aging and AD. Individuals with MCI have impairment of memory but not other cognitive or daily functions, but they are at an increased risk for developing AD at an estimated rate of 10% to 15% per year. Measuring the change of the hippocampus volume in brain MRI for individuals with MCI is a very useful way to study the conversion of MCI to AD. Therefore, the accuracy of the pixel counts for the hippocampus becomes a main concern. According to the comparisons of the batch-type LVQ and GKCL algorithms for the first two MRI data sets, FSLVQ can strip the ROI tissue from nonuniformity gain tissue. Thus, we apply FSLVQ to the third AD MRI case. A window including the hippocampus and amygdala is carefully selected. The window-selected MRI data set is tested twice for the flexibility of algorithm. Regardless of whether a set of initials from the histogram of images or a set of randomly selected initials was used, both results turned out to be a segmentation with good and accurate quality. The FSLVQ segmentation technique is quite helpful in outlining or stripping the ROI tissue and also in accurately measuring the volume of tissues. It is an efficient tool as an aid to medical diagnoses and also as a good tissue volume measurement.

Acknowledgments

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References