An experimental evaluation of echo state network for colour image segmentation

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***Abstract*— Image segmentation refers to the process of dividing an image into multiple regions which represent meaningful areas. Image segmentation is an essential step for most image analysis tasks such as object recognition and tracking, pattern recognition, content-based image retrieval, etc. In recent years, a large number of image segmentation algorithms have been developed, but achieving accurate segmentation still remains a challenging task. Recently, reservoir computing (RC) has drawn much attention in machine learning as a new model of recurrent neural networks (RNN). Echo State Network (ESN) represents one efficient realization of RC, which is initially designed to facilitate learning in Recurrent Neural Networks. In this paper we investigate the viability of ESN as feature extractor for pixel classification based colour image segmentation. Extensive experiments are conducted on real world colour image datasets and the global ESN reservoir parameters are varied to identify their operating ranges that allow the use of the reservoir nodes internal activations as new pixel features for the colour image segmentation task. A simple feed forward neural network is used to realize the ESN readout function and classify these new features. The experimental results show that the proposed method achieves high performance image segmentation comparing with state-of-the-art techniques. In addition, a set of empirically derived guidelines for setting the reservoir global parameters are proposed.**

Keywords—echo state network; colour image segmentation; pixel classification; feature extraction.

I. Introduction

Image segmentation is the process of dividing an image into homogeneous regions which represents meaningful areas of the image. This is done using image characteristics such as intensity, texture or location . Image segmentation is an essential step for successful image analysis and understanding. It has a wide range of applications including medical imaging, object recognition and tracking, satellite imaging, content based image retrieval, to name but a few. Due to its importance, a large number of segmentation algorithms have been developed [1,2,3 and 4], however, accurate segmentation still remains a challenging due to the complexity usually accompanies this process such as overlaps between intensities of different objects, intensity inhomogeneity, presence of noise, variation of contrast and weak edges.

Recently, reservoir computing (RC) [5, 6] has drawn much attention in machine learning community as a new computational framework for recurrent neural networks (RNN) due to the simplicity of its training. One possible realization of RC is the echo state network (ESN) proposed by Herbert Jaeger [7], which consists of a large randomly generated untrained RNN followed by a readout layer that is trained using linear regression algorithms. Despite the simplicity of the ESN concept, it has been successfully applied in many tasks such as time series prediction [8], traffic load prediction [9], detection of weak signal embedded in chaotic background [10], image segmentation [11], spectral images clustering [12] and microscopic cellular image segmentation [13]. Another similar approach to ESN is the Liquid State Machine (LSM) which has been proposed by Maass et al. [14]. The nodes of the recurrent network in ESN use rate-based neurons unlike LSM where spiking neurons are used instead.

In this paper we investigate the viability of the ESN framework for colour image segmentation. We have designed an ESN which consists of a reservoir to act as image features extractor, and a simple feed forward neural network to realise the ESN readout function and classify the image features captured by the reservoir output nodes. We have thoroughly explored the parameter space of the ESN reservoir by conducting extensive experiments on real world image datasets to identify the optimal operating range of its main parameters for achieving high performance colour image segmentation. The segmentation produced by the proposed approach is evaluated using objective segmentation quality metric. Segmented images are compared against their ground truth counterparts (expert manual segmentation) and the F-score metric is used to measure the segmentation accuracy. The obtained results are promising and indicate that the proposed ESN based approach is effective for colour image segmentation and can achieve high segmentation accuracy that outperforms the state of the art methods. Another interesting finding of this research shows that a small group of neurons randomly selected from the reservoir outputs can extract good image features enough for achieving adequate segmentation performance.

The rest of the paper is organized as follows. Section 2 presents an overview of related work relevant to the proposed approach. The concept of ESN and its main parameters are described in section 3, and section 4 introduces the proposed ESN based approach and its application to colour image segmentation. Section 5 presents a series of experiments conducted to validate the proposed approach and explore the effect of the reservoir global parameters on the accuracy of image segmentation. The obtained results and comparisons with state of the art image segmentation methods are also presented in this section. Section 6 concludes the paper and discusses possible future extensions of this work.

II. RELATED WORK

Image segmentation techniques can be divided into five major categories: thresholding based segmentation, region based segmentation, edge based segmentation, clustering based segmentation and pixel classification based segmentation [3, 15, and 16].

Thresholding is a popular image segmentation method that converts an image into a binary image using a threshold. Usually this method requires analysis of the image histogram to extract the different modes, searching the valleys of these modes and applying thresholds to the image according to the found valleys. However, it was found that this approach did not work well with images having unimodal or nearly unimodal histograms and ambiguous partitions are produced in the presence of noisy peaks. Additionally, for colour images, the thresholding in a multidimensional space is a difficult task.

Region-based segmentation techniques divide an image into subsets where the neighbouring pixels within one subset are similar according to a certain defined criterion. The most popular region-based segmentation techniques are the region growing and region splitting and merging [16]. Region-based segmentation methods are simple compared to other methods and also noise resilient. However the computational requirement for these methods remains high, and the resulting segmentation, in general, leads to non smooth and badly shaped boundaries for the segmented objects.

In edge based image segmentation, the edges refer to the pixels at which there is an abrupt change in intensity or texture and an image is segmented by detecting those discontinuities. Edge detection algorithms are, however, very sensitive to noise and can result in detection of fake edges and true edges being missed.

Clustering based image segmentation is the task of grouping a set of pixels in such a way that pixels in the same cluster are more similar to each other than to those in other clusters. This is achieved by various algorithms that differ significantly in their notion of what constitutes a cluster and how to efficiently find them. The most widely used clustering algorithms include k-means [17] and fuzzy C-means [18]. However, these techniques are computationally excessive and require prior knowledge of the number of clusters in the image.

Colour image segmentation can also be viewed as an image pixel classification problem where each pixel is characterised by a number of features such as colour, intensity or texture. In this approach, a classifier is used to assign a label to every pixel in an image such that the same label is given to pixels having similar features. Classifiers such as Neural networks and Support Vector Machines (SVM) have been utilized successfully in pixel classification based image segmentation [19]. They usually result in high segmentation accuracy, however they need a training period and the results depends on connections weights initialisation.

The idea of using the ESN for image segmentation has been explored in previous studies. Suganthi and Purushothaman [11] have applied the ESN to FMRI segmentation. They extracted statistical features from fMRI image data and used an ESN for binary classification of the extracted features. They obtained better segmentation performance with higher peak signal to noise ratio (PSNR) when compared to that obtained by the back-propagation algorithm (BPA). However, the evaluation of this approach has been limited to binary classification of grey scale images.

Meftah et al. [13] have successfully applied the ESN to segmentation of microscopic cellular images. They have used two separate reservoirs to segment the images into three classes (areas), namely the nucleus, the cytoplasm and the background. One reservoir separates background from both cytoplasm and nucleus and the second separates nucleus from both background and cytoplasm. Each pixel is assigned to one winning class background versus rest or nucleus versus rest, then a superposition based on maximum operator (the max value of the activation function from the readouts of both reservoirs) is used to decide the winning class. The authors reported their proposed approach proved effective for cellular image segmentation where the number of classes is small (three classes). However it has not been demonstrated on segmentation involving a higher number of classes where a big number of reservoirs (one class versus rest) would be required and can increase the computational complexity of the system. In addition, the single reservoir used in this study is not fine-tuned; hence further evaluation is required to demonstrate the performance of the proposed computationally complex multi-reservoir approach.

Koprinkova et al [12] have used the ESN as features extractor for clustering of multi-spectral satellite images. Firstly, the ESN reservoir parameters are improved using the intrinsic plasticity (IP) based adaptation. Secondly, they project the original inputs (seven features for each pixel) on the improved reservoir and only two neurons from the reservoir are considered as new features. To choose the couple of neurons which have more relevant information from the original inputs, two dimensional probability density distribution of all possible combinations between every two neurons of the reservoir is estimated using Kernel Density Estimation via diffusion approach [20]. Then the couple of neurons having the probability density distribution with highest number of local maxima (which contain the maximum of peaks) are selected. The process of clustering is then applied to the new features represented by the outputs of the two selected neurons. A qualitative evaluation of resulting segmentation showed that the obtained clusters of a multispectral satellite image of a mountain region in Bulgaria are similar to the results given by the Ministry of Regional

Development and Public Works of Bulgaria. However, this technique requires an excessive computational load primarily due to the number of possible neuron pairs from the reservoir which amounts to $n(n-1)/2$ possibilities, where n is the number of reservoir neurons, and the need to compute a two dimensional probability density distribution for each pair of neurons.

III. ECHO STATE NETWORK

A. Basic approach

The architecture of the ESN (illustrated in Fig. 1) consists of three layers: an input layer, an internal layer (also known as dynamical reservoir) and an output layer often called the read-out layer [7]. The input data is fed into the reservoir through random synaptic input connections (W_{in}). The reservoir contains a large number of nodes (N nodes) sparsely connected with randomly weighted connections (W_{int}). The output layer contains L output nodes connected with the reservoir through output weights (W_{out}).

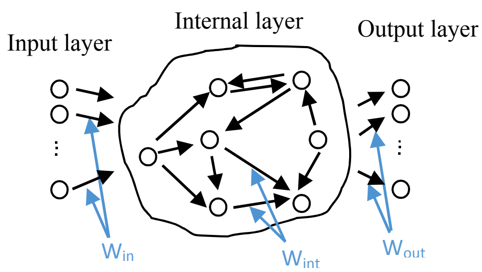


Fig. 1. Generic ESN architecture

When an input data (u) is fed into the network, the reservoir internal state (x) is updated according to the following formula:

$$x\ (n+1) = f\,(W_{int} \times x(n) + W_{in} \times u(n+1)) \quad (1)$$

Where $x(n+1)$ and $x(n)$ are the internal states of the reservoir at time steps n+1 and n, respectively, W_{int} is the matrix of connection weights between reservoir nodes with size of $N\times N$, W_{in} is the matrix of input connection weights of size $K\times N$, $u(n+1)$ is the input data at time step $n+1$, $(u(n+1) = \{u_j(n+1) : j = 1, \ldots, K\})$, f is the activation function of the reservoir nodes, typically a hyperbolic tangent or another sigmoidal function. The input and internal matrices are randomly initialized and remain unchanged during the training of the readout and use of ESN.

The network output $y(n+1)$ is computed through the following equation:

$$y\ (n+1) = g(W_{out}\ x(n+1)) \quad (2)$$

Where W_{out} is a matrix of the output connection weights with size of $N\times L$ and g indicates the activation function of the output neurons, generally designated to be a linear function.

Unlike recurrent neural networks which are trained using backpropagation through time, the main advantage of the ESN is the simplified training algorithm which involves to update only the output layer (readout) weights, after presenting the input data to the network and collecting the reservoir states, the weights of the connections from the reservoir to the readout neurons are adjusted by minimizing the mean squared error between the actual output Y and the desired output Y_d with any of the available algorithms for linear regression [7]:

$$W_{out}=arg_w(min\|Y - Y_d\|^2) \quad (3)$$

Where $\|.\|$ denotes the Euclidean norm. The readout matrix W_{out} s is given by:

$$W_{out}= (X^TX)^{-1}X^TY_d \quad (4)$$

Where X is a matrix contains all the reservoir states, X^T denotes the transpose of X and $(X^T X)^{-1}$ denotes the inversion of square matrix $X^T X$.

However in the presented work we have used a multi-layer perceptron (MLP) as a readout layer to process the collected data from the reservoir outputs.

B. ESN reservoir parameters

While the ESN is practical and simple to implement, its performance is closely linked with the tuning of initial parameters. Therefore, it is important that these parameters are set appropriately before using the ESN.

The ESN reservoir can be considered as a high dimensional projection of the input data $u(n)$ which is initially not linearly separable. It is hoped that the new data presented by the internal state of the reservoir $x(n)$ can be separated by a simple linear regression if adequate reservoir parameters are used.

At the same time the reservoir can be considered as a short term memory where each input $u(n)$ is memorized in the internal state of the reservoir, $x(n)$, and is considered for computing the new state of the reservoir, $x(n+1)$, when the next input $u(n+1)$ is presented.

Three common global reservoir parameters are studied in this paper:

1) The connectivity between the reservoir neurons: In our experiments, we have used random connections between reservoir neurons with a given connectivity density defining the distribution of nonzero elements in the matrix of connections weights between reservoir neurons W_{int}. This parameter has influence on the ESN complexity. A big number of connections leads to an increase in the number of operations required for computing the reservoir output.

2) The reservoir size: it represents the number of neurons in the reservoir (also called the reservoir dimension). In this work, we have varied this parameter starting with smaller reservoirs then scaling it up to bigger sizes.

3) The spectral radius: This parameter is a commonly used indicator for the Echo State Property [22] which means that the system forgets its inputs after a limited amount of time, i.e. the reservoir state depends on the inputs rather than on its initial conditions. The spectral radius is defined by the maximum absolute value of eigenvalues $|\lambda_{max}|$ of the reservoir weights matrix W_{in} [21]. The effects of this important reservoir parameter on the accuracy of image segmentation are also studied in this paper.

IV. THE PROPOSED ESN-BASED COLOUR IMAGE SEGMENTATION APPROACH

In colour image segmentation by pixel classification, a region is defined by the set of connected pixels belonging to the same class. Several pixel features can be used for classifying a given pixel into an image region (pixel based segmentation). In all the experiments presented in this paper, we have used very simple low level pixel features which are replaced with the internal reservoir activations after being fed to the ESN, i.e. the ESN projects these simple input features into a new set of features represented by its internal reservoir activations. As shown in Fig, 2, for each pixel we have extracted five features: three chromatic features (R, G and B pixel components) in addition to two spatial features, namely the average value and the standard deviation of its neighbouring pixels within a window of 11x11 pixels. This window size is chosen through trial and error after conducting several experiments using different window sizes. The five features are calculated for each pixel and are normalized between 0 and 1, then the image pixels are fed into the ESN and the reservoir outputs are used as new pixel features for classification.

A group of pixels selected from the image, represented by the new features provided by the reservoir output matrix is used to train an MLP with the ground truth segmentation of the input image being used as desired outputs (details on the training set size and the strategy of its selection are presented in the next section). We have used the Levenberg-Marquardt backpropagation algorithm to update the connections weights during the training of the readout. The trained readout is then used to classify the remaining pixels of the image and assign a region label to each pixel.

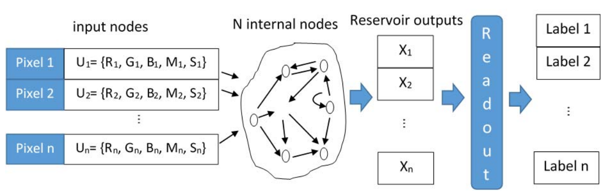


Fig. 2. Proposed aproach for image segmentation, R_i, G_i, B_i, are Red, Green, and Blue of the pixel i and M_i, S_i are the average value and the standard deviation of neighbouring pixels of the pixel i.

V. RESULTS AND DISCUSSION

A. Experimental setup

In order to evaluate the performance of the proposed technique, extensive experiments have been conducted on two different real world image datasets: Semantic Segmentation Data Set (SSDS) [23] and Segmentation Evaluation Dataset (SED) [24]. The SSDS includes 100 images of 321 × 481 pixels with their ground-truth segmentations, selected from Berkeley Segmentation Dataset [25]. The SED contains 100 images provided in colour and in grey scale, each image contains single prominent object that differ from its surrounding by either intensity or texture. The goal is to generate a segmentation of foreground and background regions with the foreground region covering the object as accurately as possible. Figure 3 and 4 show sample images from these datasets and the corresponding ground-truth segmentations.

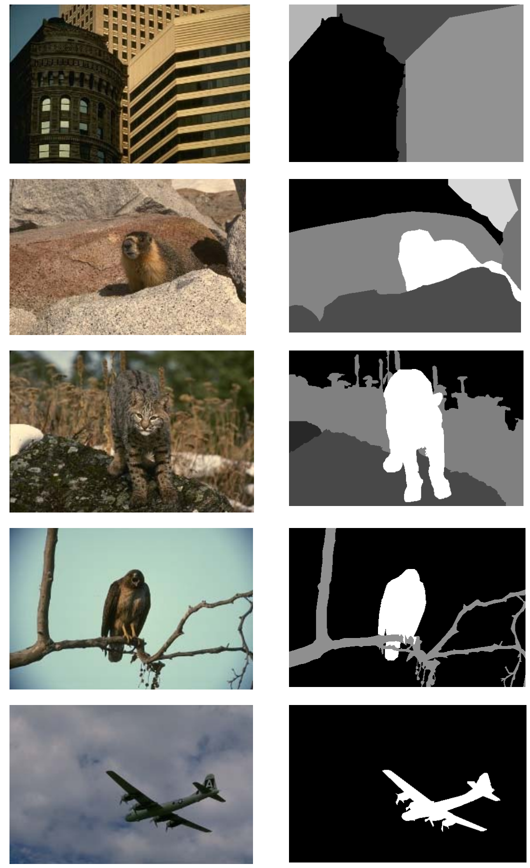


Fig. 3. Sample images from Semantic Segmentation Data Set. Original images in column (a) and corresponding ground truths in column (b)

The input and the reservoir weights of the ESN are randomly initialized between -1 and +1. Sigmoidal activation functions have been used in the reservoir nodes, in particular we have used the *tanh* function which is a common choice as described in section III.A.

We have selected randomly a group of 10 neurons from the reservoir to be used as pixel features for classification, we have conducted several experiments with different numbers of selected neurons from the reservoir and have found that 10 neurons is the minimum number of neurons required for achieving acceptable segmentation performance. An MLP is used to realise the readout function of the ESN. It consists of two hidden layers of 15 sigmoidal neurons each and an output layer of two linear neurons. This MLP configuration is also chosen by trial and error after conducting several experiments using different numbers of layers and different neurons in each layer.

There are no direct connections between the ESN input layer and its readout layer. There are no feedback connections from the readout layer to the reservoir or to the input layer.

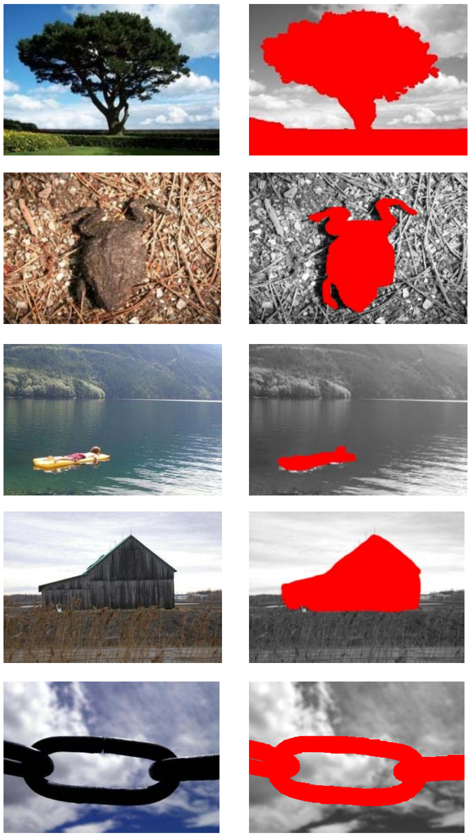


Fig. 4. Sample images from Segmentation Evaluation Dataset. Original images in column (a) and corresponding ground truths in column (b)

The training set consists of 40 % of the input image pixels. Training samples are selected using random subsampling without replacement, for each image.

In all the experiments of this paper, the segmentation accuracy of each obtained result is evaluated using the F-score metric [24] which is given in the following equation:

$$\textit{F-score} = 2\times P\times R / (P+R) \tag{5}$$

where P and R are the precision and recall values. The F-score takes values between 0 and 1 and the closest its value to 1 the better the overall segmentation accuracy. Note that the F-score metric is computed for each segmented image using all image pixels, which include the pixels used for the training.

An extensive series of experiments are conducted where the three parameters of the reservoir, described in section III.B, are varied and the segmentation accuracy of each obtained ESN is evaluated. The reservoir size is set to 50, 100, 200, 300 and 500; the spectral radius is set to 0.001, 0.01, 0.1, 0.2, 0.4, 0.6, 0.8 and 1; and the connectivity density is varied from 0.2 to 1 with a step of 0.2. The readouts of all of the obtained 200 ESNs are trained and tested on all of the 100 images of the SSDS dataset, each experiment is repeated five times and the mean performance is computed, giving a total of 100000 experiments. The obtained results are presented and discussed in the following section.

B. *Influence of reservoir global parameters on image segmentation performance*

Fig.5 shows the obtained mean F-score results for different values of the reservoir parameters. Each panel shows the mean F-score as a function of the reservoir dimension and the spectral radius for a fixed density value of the connectivity between the reservoir nodes.

It is known that the segmentation quality depends on the quality of the pixel features. Therefore, these results allow us to evaluate the segmentation quality based on the features extracted by the reservoir, and consequently identify the operating ranges of these reservoir parameters which provide adequate features for high performance colour image segmentation.

It can be seen from Fig.5 that all panels show overall comparable performance results irrespective of the value of the reservoir connectivity density parameter. Therefore, it appears that the connectivity density of the reservoir doesn’t seem to greatly affect the segmentation performance. Consequently, small connectivity values are preferable in this case as they result in a less complex ESN.

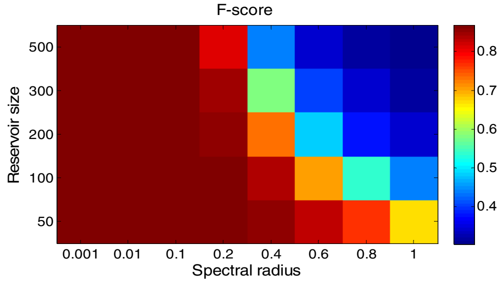
In addition, small values of the spectral radius between 0.001 and 0.1 have been found to give the best segmentation performances (an F-score between 0.8102 and 0.8686). For instance, panel (a) shows that, regardless of the reservoir size, an ESN with a connectivity of 0.2 and a spectral radius between 0.001 and 0.1 can achieve an F-score between 0.8639 and 0.8686.

Furthermore, it is found that for a spectral radius of 0.2 the obtained performance is high when the size of the reservoir is small, however the segmentation performance degrades when the value of the reservoir size increases. For example, according to panel (a) corresponding to a reservoir connectivity of 0.2, a spectral radius of 0.2 results in a performance of 0.8678 when the reservoir size is set to 50. This performance then decreases to 0.8482 and 0.8156 when the reservoir size is set to 300 and 500, respectively. The segmentation performance also decreases for values of the spectral radius greater than 0.2 and particularly when the reservoir dimension is increased.

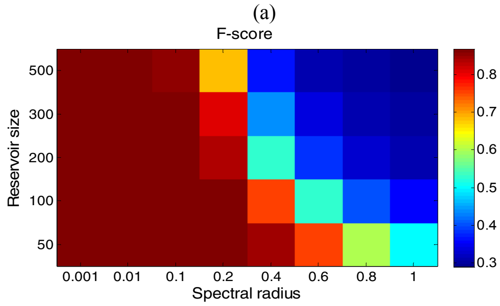
The best F-score value obtained across all the different values of the three global parameters of the reservoir is 0.8687. It has resulted from an ESN with a connectivity density of 0.2, a spectral radius of 0.1 and a reservoir size of 100 neurons.

Another important finding of this study is that the use of a small group of 10 nodes randomly selected from the reservoir to be used as pixel features resulted in a reliable segmentation. For each image and for each chosen triplet of the reservoir parameters, the experiment is repeated five times where the maximum standard deviation for all images is 0.0176 (corresponding to a mean F-score of 0.8033). This small value of the standard deviation proves that even random selection of a small number of neurons from the reservoir can provide adequate features for good quality image segmentation, unlike the work in [12], discussed in section II, where the selection of neurones from the reservoir requires an excessive computational load.

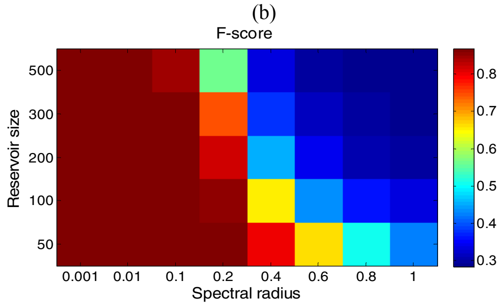
On the basis of these results, one can make an informed choice of the global parameter values of the ESN reservoir which can provide a trade-off between adequate pixel features for quality colour image segmentation task and computational complexity.



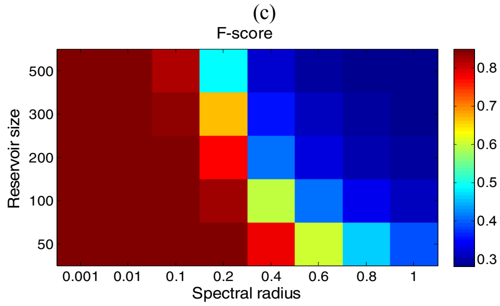
(a)



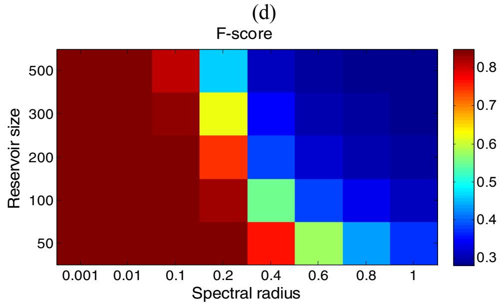
(b)



(c)



(d)



(e)

Fig. 5. The mean F-score value as a function of the reservoir dimension and the spectral radius for different values of the connectivity density.
(a) connectivity density=0.2, (b) connectivity desnity=0.4, (c) connectivity density=0.6, (d) connectivity density=0.8 (e) connectivity desnity =1.

Based on this experimental evaluation, it appears that the best design choice of ESN reservoirs for good quality colour image segmentation and low complexity consists of using a spectral radius that is less than or equal to 0.2, a connectivity density of 0.2 with a reservoir dimension between 50 and 100 neurons.

We will use these experimentally derived guidelines for testing the proposed system further on another image dataset and comparing it with other state of the art image segmentation methods. These further benchmarking experiments are presented in the following section.

C. *Comparison with other methods*

The proposed ESN-based colour image segmentation approach is evaluated further on another image dataset, namely the Segmentation Evaluation Dataset (SED). A few sample images from this dataset and their corresponding ground truth segmentation are shown in Fig. 4. The results of the ESN based colour image segmentation are compared with existing state of the art image segmentation methods [24, 26, 27, 28, and 29]. All images in the SED dataset and the scores obtained by these methods are available online [30].

The ESN used in the following experiments is built using the guidelines derived empirically in the previous section for setting the reservoir parameters. Therefore, we have set the Echo State Network parameters as follows: the connectivity density is set to 0.2, the spectral radius is set to 0.1 and the reservoir size is set to 100 neurons. Furthermore, only 10 nodes randomly selected from the reservoir outputs are used as pixel features for classification. The readout employed in this experiment is similar to the one used earlier (i.e. an MLP containing two hidden layers with 15 sigmoidal neurons for each layer and two output neurons with linear activation functions). The proposed approach is evaluated on all 100 images of the dataset, the mean value of the F-score and the standard deviation are reported in Table I. It can be seen that the proposed ESN-based segmentation approach achieved the highest performance and clearly outperforms all the other state of the art methods.

TABLE I. EVALUATION OF SEGMENTATION PERFORMANCE OF THE PROPOSED ESN-BASED APPROACH ON THE SED DATASET AND ITS COMPARISON AGAINST EXISTING STATE OF THE ART METHODS

Algorithm	Average F-measure
ESN	0.91 ± 0.016
Scheme [26]	0.87 ± 0.010
Scheme [24]	0.86 ± 0.012
SWA [27]	0.83 ± 0.016
Normalized Cuts [28]	0.72 ± 0.018
Mean Shift [29]	0.57 ± 0.023

Alpert et al. [24] calculated the F-score using two evaluation schemes: the first scheme is based on a single segment that best fits the foreground; the second scheme takes into account a number of fragments whose union largely overlaps with the foreground object. In this paper, we carried out both types evaluation schemes and similar results are obtained. Therefore, we report only the results of the single segment.

In addition, Fig. 6 shows some segmentation samples obtained using the proposed ESN-based approach. It can be seen that the proposed approach gave a segmentation very close to the ground truth segmentations, however as most of other machine learning based image segmentation methods, the proposed approach has also produced an over segmentation in some examples as illustrated in Fig. 7.

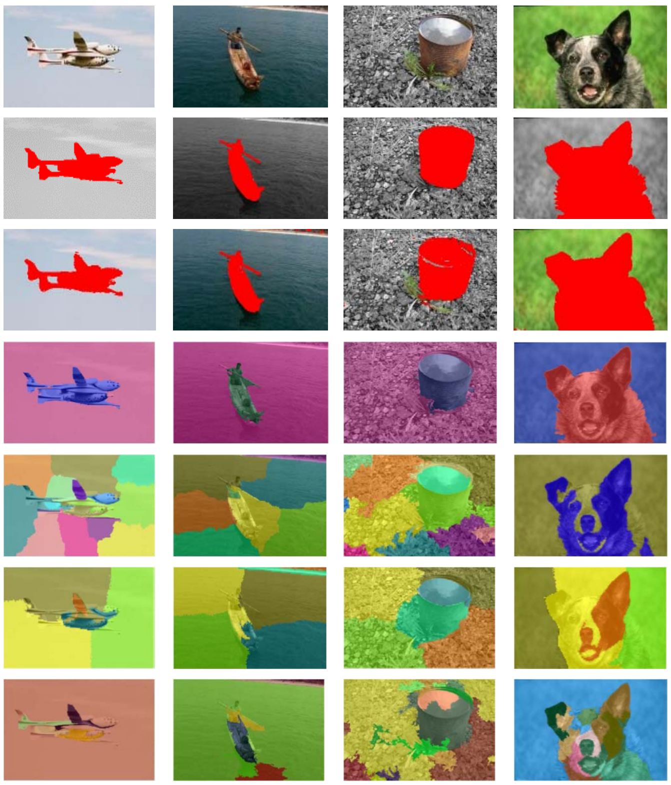


Fig. 6. Qualitative comparison of the proposed method segmentation results with those of other state of the art approachs. From top to bottom: original images, ground truth segmentation, the proposed ESN-based method, scheme [24], SWA[27], normalized cuts [28] and mean shift[29].

Fig. 7. A sample from our segmentation results producing over segmentation, From left to right : original image, corresponding ground truth and the proposed ESN-based method.

VI. Conclusion

In this paper, the ESN framework has been applied to the problem of natural colour image segmentation. We have investigated the potential of the basic internal dynamics of the ESN reservoir in extracting new adequate pixel features for image segmentation to replace the simple features originally extracted from the input image. An extensive experimental study was carried out using real world image datasets to first evaluate the effects of the ESN reservoir global parameters on the quality of the extracted features and the segmentation performance, and secondly to identify their optimal operating range and derive general guidelines for appropriately setting these parameters when applying ESN to colour image segmentation. It was found that a reservoir with random sparsely connected nodes, a small spectral radius (less than or equal to 0.2) and a medium size (between 50 to 100 neurons) can provide quality pixel features and achieve competitive segmentation performance when compared against other state of the art image segmentation methods. The presented study can be used as a practical guide to the selection of the ESN parameters for future applications to colour image segmentation.

We have also demonstrated that a small group of randomly selected nodes from the ESN reservoir can provide adequate image features for pixel classification based colour image segmentation. The obtained initial results are promising and comparative evaluation has shown that the proposed approach outperforms other state of the art methods.

This work is still ongoing and further work is planned to extend the evaluation of the proposed approach to other datasets and conduct further comparisons with other image segmentation methods using other classifiers as the ESN readout.

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