Reservoir Computing Approach for Gray Images Segmentation

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Abstract—The paper proposes a novel approach for gray scale images segmentation. It is based on multiple features extraction from single feature per image pixel, namely its intensity value, using Echo state network. The newly extracted features - reservoir equilibrium states - reveal hidden image characteristics that improve its segmentation via a clustering algorithm. Moreover, it was demonstrated that the intrinsic plasticity tuning of reservoir fits its equilibrium states to the original image intensity distribution thus allowing for its better segmentation. The proposed approach is tested on the benchmark image Lena.

Index Terms—reservoir computing, Echo state network, intrinsic plasticity, image segmentation

I. INTRODUCTION

Echo state networks (ESN) belong to a novel and rapidly developing family of reservoir computing approaches [1]–[3] whose primary aim was development of fast trainable recurrent neural network (RNN) architectures able to approximate nonlinear time series dependencies.

Following different view point to dynamic reservoir structure and its properties, in [4] a novel approach for features extraction from multidimensional data sets using ESN was proposed. It was successfully tested on numerous practical examples, among which clustering and segmentation of multispectral images [5]. Similar works dealing with ESN features extraction for image segmentation were reported in [6]–[9]. Other works propose to train ESN to classify image pixels based on their preliminary extracted features [10]–[15]. All these works are focused on colour image segmentation having multiple features per pixel, e.g. RGB grades. The gray scale images however have a single feature per pixel that is its intensity.

The aim of the presented here investigation is to adapt the reservoir approach from [4] to uni-dimensional features data such as gray scale images and to test whether such an approach could enhance gray images segmentation via clustering. The core of the approach in [4] was to use the reservoir equilibrium states corresponding to each one of the multidimensional feature vectors as new, hopefully better feature vector of different dimension. Fitting the ESN to reflect the input data structure was achieved using an approach for tuning of reservoir internal connectivity called Intrinsic Plasticity (IP) [16], [17].

In present work the IP tuned ESN reservoir with one dimensional input (pixel intensity) was exploited to extract multiple features per pixel (reservoir equilibrium states) of a gray image. The approach was investigated in details on a famous image called "Lena" that was benchmark subject in numerous image processing and analyses techniques. The original features and ESN extracted ones before and after IP tuning were compared with respect to their distribution as well as with respect of the quality of image segmentation via clustering by several approaches applied by far to Lena image, namely kmeans, fuzzy c-means, subtractive clustering [18], hard thresholding and multi-level image thresholding using Otsu's method [19].

The paper is organized as follows: the next section introduces ESN, IP tuning algorithm and adapted to gray scale images approach for features extraction; the following section presents obtained features of Lena image and the outcome of different clustering approaches; the paper finishes with concluding remarks and direction for future work.

II. ESN APPROACH FOR GRAY SCALE IMAGES FEATURES EXTRACTION

The structure of an ESN reservoir is shown on Fig 1.

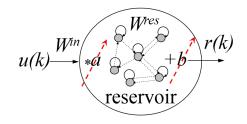


Fig. 1. ESN reservoir with parameters for IP tuning.

It incorporates a pool of neurons with sigmoid activation function f^{res} (usually the hyperbolic tangent) that has randomly generated recurrent connection weights. The reservoir state r(k) for the current time instant k depends both on its previous state r(k-1) and the current input u(k) as follows:

$$r(k) = f^{res}(diag(a)W^{in}u(k) + W^{res}r(k-1) + diag(b))$$
(1)

Here W^{in} and W^{res} are input and recurrent connection weight matrices that are randomly generated according to

recipes given by [3]; a and b are vectors called gain and bias that are set to 1 and 0 respectively in most applications.

In order to adjust the reservoir to the structure of its input data, [16], [17] proposed an approach called Intrinsic Plasticity (IP) tuning that achieves desired distribution of reservoir output via changes in the gain a and bias b in equation (1). The procedure is gradient algorithm minimizing Kullback-Leibler divergence between actual and target distributions. In case of hyperbolic tangent activation function the proper target distribution is normal (Gaussian) with mean μ and variance σ :

$$p_{norm} = (1/\sigma\sqrt{2\pi})e^{(r-\mu)^2/2\sigma^2}$$
 (2)

Thus the training rules for IP tuning of gain and bias vectors derived in [16] are:

$$\Delta a = \eta/a + \Delta bx \tag{3}$$

$$\Delta b = -\eta(-\mu/\sigma^2 + r/\sigma^2(2\sigma^2 + 1 - r^2 + \mu r)) \tag{4}$$

Here η is learning rate and $x=W^{in}u+W^{res}r$ is the net input to the reservoir neurons. The Algorithm 1 presents the IP tuning procedure. All original vectors of features $f(i), i=1 \div n_f$ are fed consecutively to the ESN reservoir with zero initial state r(0)=0 for n_{IP} IP tuning iterations (usually 3-5 are enough as in [16]). In present research, like in [4] the IP tuned reservoir neurons equilibrium states r_e are exploited. The Algorithm 2 present the features extraction procedure.

Algorithm 1 IP tuning

```
IP tuning of ESN
2: Generate initial ESN reservoir
   r(0) = 0
4: a(0) = 1
   b(0) = 0
6: for k=1\div n_{IP} do
     for i = 1 \div n_f do
        x(i) = W^{in}f(i) + W^{res}r(i-1)
8:
        r(i) = tanh(a(i-1)x(i) + b(i-1))
        a(i) = a(i-1) + \Delta a(i)
10:
        b(i) = b(i-1) + \Delta b(i)
     end for
12:
   end for
```

Algorithm 2 Features extraction

```
Extract\ features\ from\ IP\ tuned\ ESN
2:\ \textbf{for}\ i=1\div n_f\ \textbf{do}
r(0)=0
4:\ \ \textbf{for}\ k=1\div n_{it}\ \textbf{do}
x(k)=W^{in}f(i)+W^{res}r(k-1)
6:\ \ r(k)=tanh(ax(k)+b)
\textbf{end}\ \textbf{for}
8:\ \ r_e^i=r(k)
\textbf{end}\ \textbf{for}
```

All original vectors of features $f(i), i=1 \div n_f$ are fed consecutively n_{it} times as constant input $u(k)=f(i)=const., k=1 \div n_{it}$ to the ESN reservoir with zero initial state r(0)=0 until it settles to a new equilibrium state $r_e(f(i))=r(n_{it}).$ n_{it} is number of iterations needed to achieve steady state $r_e=r(k)=r(k-1)$ of the reservoir. Achieved in this way equilibrium states of the ESN reservoir r_e^i for each original features vector f(i) are considered as new features.

In [4] it was investigated how the IP tuning of a randomly generated ESN reservoir led to clearer separation of the original multidimensional data after its projection to low dimensional space. The effect of IP tuning on reservoir equilibrium state was further investigated in [20] demonstrating that it increases equilibrium states memory capacity and is strongly influenced by the original data structure.

Provoked by the needs of gray scale images clustering a modified approach for features extraction was proposed. In contrast to [4], here from each single feature per pixel (that is its intensity value $f(i) = pi(i), i = 1 \div n_{pi}$) multiple features corresponding to ESN reservoir neurons equilibrium states r_e^i were obtained. Here $n_f = n_{pi}$ is the number of the gray image pixels; pi(i) is i - th pixel intensity; The obtained in this way multidimensional feature vector r_e^i for each pixel pi(i) is subject to clustering.

III. RESULTS AND DISCUSSION

In order to investigate effects of proposed features extraction approach a benchmark image Lena was used. The original colour image was converted to gray scale and pixels intensities pi were scaled in range [-1,1]. Next, all pixels intensities were applied to tune the gain and bias parameters of a randomly generated fully connected ESN reservoir with size $n_r=10$ and spectral radius 0.9. The target Gaussian distribution of IP tuning was with zero mean and variance $\sigma=0.1$ and number of IP tuning iterations was set to $n_{IP}=5$. The number of iterations needed to achieve reservoir steady state was estimated to $n_{it}=50$.

For the seek of comparison features were extracted by initial and IP tuned reservoir as shown on Fig. 2. Fig. 3 shows histograms of the original image pixels intensities versus those of features extracted by initial and IP tuned ESN reservoirs. The observed effects of IP tuning are following: the reservoir equilibrium states were squeezed in narrow interval; the distribution of new equilibrium states reflects the original data distribution.

Next kmeans clustering algorithm was applied to separate image pixels into clusters using all original and all extracted by initial and IP tuned reservoir features. From Fig. 3 is clear that features extracted from IP tuned reservoir can be visually separated into three groups - having maximum around -0.3, 0.1 and 0.3 respectively that is in accordance other segmentation approaches tested on Lena image. So the number of clusters was set to three here. The representative features from the three groups in Fig. 3 (neurons 1, 3 and 8) were selected for clustering too.

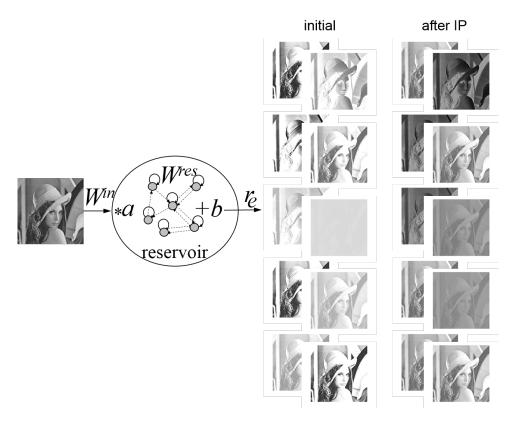


Fig. 2. Gray image features extraction.

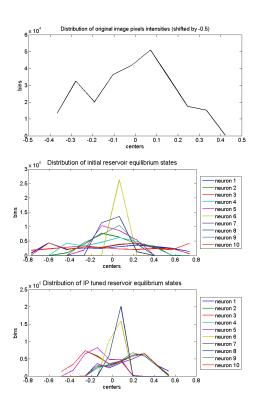


Fig. 3. Histogram of the original image pixels intensities shifted by -0.5 (top) vs. equilibrium states distributions of initial (middle) and IP tuned reservoir (bottom).

Comparison of the original gray image and its segmentation via kmeans clustering are shown in Fig. 4. While segmentation using features extracted by initial random ESN reservoir looks blurred, the results achieved using IP tuned reservoir reveal sharper discrimination between image regions. Segmentation via representative features (neurons 1, 3 and 8) seems quite similar to that achieved using all features extracted by IP tuned reservoir. Looking at Fig. 4, it is observed that the results achieved using features extracted by IP tuned reservoir look quite similar to those obtained by kmeans clustering of original image pixels intensities. However, IP tunned reservoir features revealed a little bit more details from the original image, e.g. shades on the shoulder, contours in the background stuff etc.

For the seek of comparison the gray image was segmented using original pixels intensities and several clustering approaches: kmeans, hard thresholding using fixed threshold levels equally distributed within range of pixels intensities, multi-level thresholding using Otsu's method [19], fuzzy c-means clustering and subtractive clustering [18]. Fig. 5 presents comparison of the original gray image and its segmentation by enumerated clustering approaches. It is obvious that kmeans segmentation outperforms all other approaches achieving sharper segmentation of the image.

Fig. 6 and 7 present results from kmeans clustering using individual features extracted by the initial and IP tuned reservoirs respectively.

Feature by feature comparison shows that IP tuning allows







Fig. 4. Segmentation of the original gray image (on the top) into three clusters by kmeans clustering. Second row, from left to right, represents the clustering results achieved using all features extracted by the initial reservoir (left), by the IP tuned reservoir (middle) and by it representative neurons 1, 3 and 8 (right).











Fig. 5. Segmentation of the original gray image (on the top) into three clusters using original image pixels intensities. Second row from left to right, represents the clustering results achieved via hard thresholding, multi-level threscholding, fuzzy c-means, subtractive clustering and kmeans clustering.











Fig. 6. Gray Lena image (on the top) and its segmentation from individual features extracted by initial reservoir.



Fig. 7. Gray Lena image (on the top) and its segmentation from individual features extracted by IP tuned reservoir.

to achieve sharper discrimination between regions with different grades of pixels intensities. Besides, looking at individual features results, becomes clear that each neuron acts as a filter revealing different image characteristics. For example, neuron 8 of IP tuned reservoir reveals differences in pixels intensity at the left top corner of the original image that are not reveal by anyone of the rest of exploited features while it fails do distinguish shades at the right top corner of the image.

Looking at Fig. 6 and 7 leads to the conclusion that reservoir equilibrium states can be considered as image projections from different view points in the space. Thus in dependence on some additional, e.g. expert information, a proper for a given aim projection can be chosen for image segmentation. Close comparison of segmentation results from the original and IP tuned reservoir features however is in favour of the IP tuning approach since it reveals sharper discrimination of shapes in some regions of the image, e.g. some light bunches in the hair, shades on the shoulder, contours in the background stuff etc.

IV. CONCLUSIONS

The obtained results demonstrated that the proposed approach for gray images features extraction allows to reveal various hidden features discovering different view points to the image. They can be exploited in dependence on the specific needs and opinions of the experts in particular area interested in given image segmentation.

These preliminary results are good basis for further development of hierarchical (deep) approach for gray images segmentation combining ESN and various clustering approaches.

Further investigations with different kind of gray images, e.g. X-ray photos, tomography images etc. can reveal various directions of application of the proposed approach.

Combination of blind clustering with expert knowledge could help to further refine the approach adjusting it to specific expertise needs. A prospective direction of future work is also development of a support system for experts that will be able to choose the proper image projection among the automatically generated numerous projections generated from features extracted by IP tuned reservoir.

REFERENCES

- H. Jaeger, Tutorial on training recurrent neural networks, covering BPPT, RTRL, EKF and the "echo state network" approach. GMD Report 159, German National Research Center for Information Technology, 2002.
- [2] C. Gallicchio, M. Lukosevicius, S. Scardapane, "Frontiers in reservoir computing", Proceedings of 28th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2020, Belgium, pp.559–566.
- [3] M. Lukosevicius, H. Jaeger, "Reservoir computing approaches to recurrent neural network training", Computer Science Review, vol. 3, 2009, pp.127--149.
- [4] P. Koprinkova-Hristova, N. Tontchev, "Echo state networks for multidimensional data clustering", In: Villa, A.E.P., Duch, W., Érdi, P., Masulli, F., Palm, G. (eds.) Int. Conf. on Artificial Neural Networks 2012, LNCS vol. 7552, pp.571—578.
- [5] P. Koprinkova-Hristova, "Multidimensional data clustering and visualization via Echo state networks", In: Kountchev, R., Nakamatsu, K. (eds.) New Approaches in Intelligent Image Analysis, Intelligent Systems Reference Library vol. 108, 2016, pp.93—122.
- [6] B. Meftah, O. Lézoray, A. Benyettou, "Novel Approach Using Echo State Networks for Microscopic Cellular Image Segmentation", Cognitive Computation, vol. 8, Issue 2, 1 April 2016, pp.237–245.
- [7] A. Souahlia, A. Belatreche, A. Benyettou, Z. Ahmed-Foitih, E. Benkhelifa, K. Curran, "Echo state network-based feature extraction for efficient color image segmentation", Concurrency Computation, vol. 32 (21), 2020, art. no. e5719.
- [8] A. Souahlia, A. Belatreche, A. Benyettou, K. Curran, "Blood vessel segmentation in retinal images using echo state networks", 9th International Conference on Advanced Computational Intelligence, ICACI 2017, pp.91–98.

- [9] A. Souahlia, A. Belatreche, A. Benyettou, K. Curran, "An experimental evaluation of echo state network for colour image segmentation", Proceedings of the International Joint Conference on Neural Networks, October 2016, pp.1143–1150.
- [10] C. Jayakumari, T. Santhanam, "An intelligent approach to detect hard and soft exudates using echo state neural network", Information Technology Journal, vol. 7 (2), 2008, pp.386–395.
- [11] Z.F. Khan, A.S. Al Sayyari, S.U. Quadri, "Automated segmentation of lung images using textural echo state neural networks, 2017 International Conference on Informatics, Health and Technology, ICIHT 2017, art. no. 7899012.
- [12] Z.F. Khan, N. Ganapathi, "Texture based automated segmentation of skin lesions using Echo State Neural networks", Journal of Electrical Engineering and Technology, vol. 12 (1), 2017, pp.436–442.
- [13] Z.F. Khan, S. Veeramalai, G. Nalini Priya, M. Ramesh Kumar, A. Naresh Kumar, A. Kannan, "A novel approach for segmenting computer tomography lung images using Echo State Neural Networks", Journal of Theoretical and Applied Information Technology, vol. 68 (3), 2014 pp.504–513.
- [14] M.T. Nidhi, K. Gunaseelan, "Examining the variation of vascular structure in digital fundus images using textural pattern", Personal and Ubiquitous Computing, vol. 22 (5-6), 2018, pp.961–970.
- [15] M.T. Nidhi, K. Gunaseelan, "Efficient ranking of diabetic retinopathy and glaucoma using echo state neural network and radial basis function (RBF)", Journal of Medical Imaging and Health Informatics, vol. 6 (3), 2016, pp.869–874.
- [16] B. Schrauwen, M. Wandermann, D. Verstraeten, J.J. Steil, D. Stroobandt, "Improving reservoirs using intrinsic plasticity", Neurocomputing, vol. 71, 2008, pp.1159–1171.
- [17] J.J. Steil, "Online reservoir adaptation by intrinsic plasticity for back-propagation-decoleration and echo state learning", Neural Networks, vol. 20, 2007, pp.353—364.
- [18] R. Yager, D. Filev, D., "Generation of fuzzy rules by mountain clustering", Journal of Intelligent and Fuzzy Systems, vol. 2 (3), 1994, pp.209– 219
- [19] N. Otsu, "A threshold selection method from gray-level histograms", IEEE Trans. on SMC, vol. 9 (1), 1979, pp.62–66.
- [20] P. Koprinkova-Hristova, "On effects of IP improvement of ESN reservoirs for reflecting of data structure", In: Proc. of the International Joint Conference on Neural Networks (IJCNN) 2015, IEEE, Killarney, Ireland, DOI: 10.1109/IJCNN.2015.7280703.

Reservoir Computing Approach for Gray Images Segmentation*

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Abstract. The paper proposes a novel approach for gray scale images segmentation. It is based on multiple features extraction from single feature per image pixel, namely its intensity value, using Echo state network. The newly extracted features - reservoir equilibrium states - reveal hidden image characteristics that improve its segmentation via a clustering algorithm. Moreover, it was demonstrated that the intrinsic plasticity tuning of reservoir fits its equilibrium states to the original image intensity distribution thus allowing for its better segmentation. The proposed approach is tested on the benchmark image Lena.

Keywords: Reservoir computing \cdot Echo state network \cdot Intrinsic plasticity \cdot Image segmentation.

1 Introduction

Echo state networks (ESN) belong to a novel and rapidly developing family of reservoir computing approaches [1,3,11] whose primary aim was development of fast trainable recurrent neural network architectures (RNN) aimed to approximate nonlinear time series dependencies.

Following different view point to dynamic reservoir structure and its properties, in [4] a novel approach for features extraction from multidimensional data sets using ESN was proposed. It was successfully tested on numerous practical examples, among which clustering and segmentation of multi-spectral images [6].

Similar works dealing with ESN features extraction for image segmentation were reported in [12,17,18,19]. Other works propose to train ESN to classify image pixels based on their preliminary extracted features [2,8,9,10,13,14]. However, these works are focused on colour image segmentation and few of them applied the original approach from [4].

In [7] the task for gray scale tomography images segmentation using approach from [4] was put to consideration. The core of the original approach was to use the reservoir equilibrium states corresponding to each one of multidimensional input data. Fitting of the ESN reservoir dynamics to reflect the input data structure was achieved using an approach for tuning of ESN reservoir internal

^{*} Supported by ...

connectivity and dynamics called Intrinsic Plasticity (IP) [16,20]. In present work a modified version of the approach from [6] for segmentation of gray scale images was proposed. In order to enhance original image the IP tuned ESN reservoir was exploited to extract multiple features from a single feature per pixel of a gray image that is its intensity value.

In present work the approach was investigated in details on a famous image called "Lena" that was subject to numerous image segmentation approaches. Comparison with original features and extracted ones by randomly generated ESN reservoir and its IP tuned version were compared with respect to their distribution and clustering results using kmeans algorithm. The results were compared with several clustering approaches applied by far to Lena image, namely fuzzy c-means, subtractive clustering [21], hard thresholding and multi-level image thresholding using Otsu's method [15].

The paper is organized as follows: the next section 2 introduces ESN, IP tuning algorithm and adapted to gray scale images approach for features extraction; the following section presents obtained features of Lena image and the outcome of different clustering approaches; the paper finishes with concluding remarks and direction for future work.

2 ESN approach for gray scale images features extraction

The structure of an ESN reservoir is shown on Fig 1. It incorporates a pool of neurons with sigmoid activation function f^{res} (usually the hyperbolic tangent) that has randomly generated recurrent connection weights. The reservoir state r(k) for the current time instant k depends both on its previous state r(k-1) and the current input u(k) as follows:

$$r(k) = f^{res}(diag(a)W^{in}u(k) + W^{res}r(k-1) + diag(b))$$
(1)

Here W^{in} and W^{res} are input and recurrent connection weight matrices that are randomly generated according to recipes given by [11]; a and b are vectors called gain and bias that are set to 1 and 0 respectively in most applications.

In order to adjust the reservoir to the structure of its input data, [20,16] proposed an approach called Intrinsic Plasticity (IP) tuning that achieves desired distribution of reservoir output via changes in the gain a and bias b in equation (1). The procedure is gradient algorithm minimizing Kullback-Leibler divergence between actual and target distributions. In case of hyperbolic tangent activation function the proper target distribution is Gaussian one.

For the aim of time series modelling the readout of reservoir is a linear combination of its current state whose parameters are the only trainable parameters of this recurrent neural network structure. In present research however, like in [4] only the reservoir neurons equilibrium states are exploited. All original vectors of features f_i , $i = 1 \div n_f$ are fed consecutively n_{it} times as constant input $u(k) = f_i = const., k = 1 \div n_{it}$ to the ESN reservoir with zero initial state r(0) = 0 until it settles to a new equilibrium state $r_e(f_i) = r(n_{it})$. Achieved

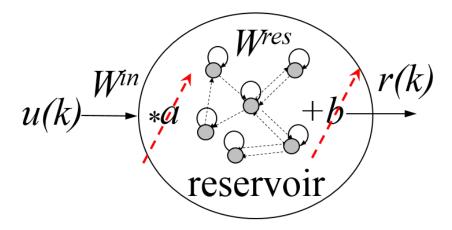


Fig. 1. ESN reservoir with parameters for IP tuning.

in this way equilibrium states of the ESN reservoir r_e^i for each original features vector f_i are considered as new features.

In [4] it was investigated how the IP tuning of a randomly generated ESN reservoir led to clearer separation of the original multidimensional data after its projection to low dimensional space. The effect of IP tuning on reservoir equilibrium state was further investigated in [5] demonstrating that it increases equilibrium states memory capacity and is strongly influenced by the original data structure.

Provoked by the needs of gray scale images clustering in [7], a modified approach for features extraction was tested. In contrast to the original work [4], in current work from each single feature per pixel (that is its intensity value $pi(i), i = 1 \div n_{pi}$) multiple features corresponding to ESN reservoir neurons equilibrium states r_e^i were obtained. The Algorithm 1 for features extraction from gray image is summarized below.

Here n_{pi} denotes number of gray image pixels; pi(i) is i-th pixel intensity; n_{IP} is number of IP tuning iterations and n_{it} is number of iterations needed to achieve steady state $r_e = r(k) = k(k-1)$ of the reservoir. The obtained in this way multidimensional feature vector r_e^i for each pixel pi(i) is subject to clustering.

3 Results and discussion

In order to investigate effects of proposed features extraction approach a benchmark image of Lena was used. The original colour image was converted to gray scale and pixels intensities pi were scaled in range [-1,1]. Next, all pixels intensities were applied to tune the gain and bias parameters of a randomly generated fully connected ESN reservoir with size $n_r=10$ and spectral radius 0.9. The target distribution of IP tuning was Gaussian with zero mean and variance $\sigma=0.1$

Algorithm 1 Pseudo code of the proposed approach

```
IP tuning of ESN
2: Generate initial ESN reservoir
   r(0) = 0
 4: for k = 1 \div n_{IP} do
      for i = 1 \div n_{pi} do
         r(k) = f^{res}(diag(a)W^{in}pi(i) + W^{res}r(k-1) + diag(b))
         Adjust vectors a and b
      end for
8:
    end for
10: Extract features from IP tuned ESN
   for i = 1 \div n_{pi} do
      r(0) = 0
      for k = 1 \div n_{it} do
         r(k) = f^{res}(diag(a)W^{in}pi(i) + W^{res}r(k-1) + diag(b))
14:
      end for
16:
      r_e^i = r(k)
   end for
```

and number of IP tuning iterations was set to $n_{IP} = 5$. The number of iterations needed to achieve reservoir steady state was estimated to $n_{it} = 50$.

For the seek of comparison features were extracted by initial and IP tuned reservoir as shown on Fig. 2. Fig. 3 shows histograms of the original image pixels intensities versus those of features extracted by initial and IP tuned ESN reservoirs. The observed effects of IP tuning are following: the reservoir equilibrium states were squeezed in narrow interval; the distribution of new equilibrium states reflects the original data distribution.

Since in most segmentation approaches tested on Lena image, it was shown that clustering into three classes achieves better results, next kmeans clustering algorithm was applied to separate image pixels into three classes using all original and all extracted by initial and IP tuned reservoir features. Since from Fig. 3 is clear that features extracted from IP tuned reservoir can be visually separated into three groups - having maximum around -0.3, 0.1 and 0.3 respectively, representative features from these three groups (neurons 1, 3 and 8) were selected for clustering too. Comparison of the original gray image and its segmentation via kmeans clustering with are shown in Fig. 4. While segmentation using features extracted by initial random ESN reservoir looks blurred, the results achieved using IP tuned reservoir reveal sharper discrimination between image regions. Segmentation via representative features (neurons 1, 3 and 8) seems quite similar to that achieved using all features extracted by IP tuned reservoir.

Fig. 5 and 6 present results from kmeans clustering using individual features extracted by the initial and IP tuned reservoirs respectively.

Feature by feature comparison shows that IP tuning allows to achieve sharper discrimination between regions with different grades of pixels intensities. Besides, looking at individual features results, becomes clear that each neuron acts as a filter revealing different image characteristics. For example, neuron 8 of IP tuned

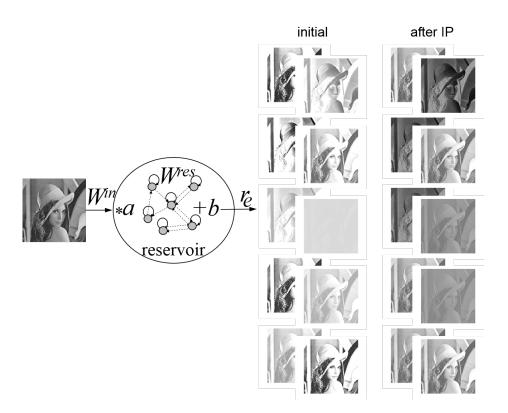


Fig. 2. Gray image features extraction.

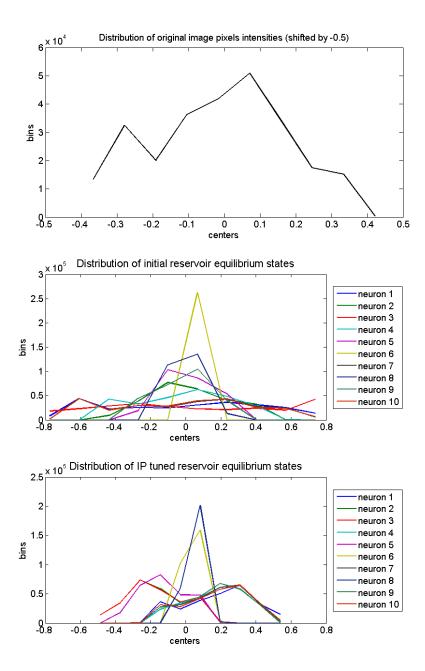


Fig. 3. Histogram of the original image pixels intensities shifted by -0.5 (top) vs. equilibrium states distributions of initial (middle) and IP tuned (bottom) reservoir.



Fig. 4. Segmentation of the original gray image (on the top) into three clusters. Second row from left to right, represents the kmeans clustering result achieved using all features extracted by the initial reservoir (left), by IP tuned reservoir (middle) and using equilibrium states of representative neurons 1, 3 and 8 from IP tuned reservoir (right) respectively.

reservoir reveals differences in pixels intensity at the left top corner of the original image that are not reveal by anyone of the rest of exploited features while it fails do distinguish shades at the right top corner of the image.

Looking at Fig. 5 and 6 leads to the conclusion that reservoir equilibrium states can be considered as image projections from different view points in the space. Thus in dependence on some additional, e.g. expert information, a proper for a given aim projection can be chosen for image segmentation. Close comparison of segmentation results from the original and IP tuned reservoir features however is in favour of the IP tuning approach since it reveals sharper discrimination of shapes in some regions of the image, e.g. some light bunches in the hair, shades on the shoulder, contours in the background stuff etc.

For the seek of comparison the same gray image was segmented using original pixels intensities and several clustering approaches: kmeans, hard thresholding using fixed threshold levels equally distributed within range of pixels intensities, multi-level thresholding using Otsu's method [15], fuzzy c-means clustering and subtractive clustering [21]. Fig. 7 presents comparison of the original gray image and its segmentation by enumerated clustering approaches.

It is obvious that kmeans segmentation outperforms all other approaches achieving sharper segmentation of the image. Looking at Fig. 4, it is observed that the results achieved using features extracted by IP tuned reservoir look quite similar to those obtained by kmeans clustering of original image pixels intensities. However, IP tunned reservoir features revealed a little bit more details from the original image, e.g. shades on the shoulder, contours in the background stuff etc.



 $\bf{Fig.\,5.}$ Gray Lena image (top) and its segmentation from individual features extracted by initial reservoir.



 ${\bf Fig.\,6.}$ Gray Lena image (top) and its segmentation from individual features extracted by IP tuned reservoir.



Fig. 7. Segmentation of the original gray image (on the top) into three clusters using original image pixels intensities. Second row from left to right, represents the clustering result achieved via hard thresholding and multi-level thresholding. Third row from left to right represents results from fuzzy c-means, subtractive clustering and kmeans clustering respectively.

4 Conclusions

The obtained results demonstrated that the proposed approach for gray images features extraction allows to reveal various hidden features discovering different view points to the image. They can be exploited in dependence on the specific needs and opinions of the experts in particular area interested in given image segmentation.

These preliminary results are good basis for further development of hierarchical (deep) approach for gray images segmentation combining ESN and various clustering approaches.

Further investigations with different kind of gray images, e.g. X-ray photos, tomography images etc. can reveal various directions of application of the proposed approach.

Combination of blind clustering with expert knowledge could help to further refine the approach adjusting it to specific expertise needs. A prospective direction of future work is also development of a support system for experts that will be able to choose the proper image projection among the automatically generated numerous projections generated from features extracted by IP tuned reservoir.

References

- Jaeger, H., Tutorial on training recurrent neural networks, covering BPPT, RTRL, EKF and the "echo state network" approach. GMD Report 159, German National Research Center for Information Technology (2002)
- Jayakumari, C., Santhanam, T., An intelligent approach to detect hard and soft exudates using echo state neural network, Information Technology Journal, 7 (2), (2008) pp. 386-395.
- 3. Gallicchio, C., Lukosevicius, M., Scardapane, S., Frontiers in reservoir computing, Proceedings of 28th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2020, Belgium, pp. 559-566 (2020)
- Koprinkova-Hristova, P., Tontchev, N., Echo state networks for multidimensional data clustering, In: Villa, A.E.P., Duch, W., Érdi, P., Masulli, F., Palm, G. (eds.) Int. Conf. on Artificial Neural Networks 2012, LNCS vol. 7552, pp. 571–578. Springer, Heidelberg (2012)
- 5. Koprinkova-Hristova, P., On effects of IP improvement of ESN reservoirs for reflecting of data structure. In: Proc. of the International Joint Conference on Neural Networks (IJCNN) 2015, IEEE, Killarney, Ireland, DOI: 10.1109/IJCNN.2015.7280703 (2015)
- Koprinkova-Hristova, P., Multidimensional data clustering and visualization via Echo state networks, In: Kountchev, R., Nakamatsu, K. (eds.) New Approaches in Intelligent Image Analysis, Intelligent Systems Reference Library vol. 108, pp. 93–122. Springer, Cham (2016)
- Koprinkova-Hristova, P., Georgiev, I., Image segmentation via Echo state network, BGSIAM'2019, Book of abstracts.

- Khan, Z.F., Al Sayyari, A.S., Quadri, S.U., Automated segmentation of lung images using textural echo state neural networks, 2017 International Conference on Informatics, Health and Technology, ICIHT 2017, art. no. 7899012, (2017).
- 9. Khan, Z.F., Ganapathi, N., Texture based automated segmentation of skin lesions using Echo State Neural networks, Journal of Electrical Engineering and Technology, 12 (1), pp. 436-442 (2017).
- 10. Khan, Z.F., Veeramalai, S., Nalini Priya, G., Ramesh Kumar, M., Naresh Kumar, A., Kannan, A., A novel approach for segmenting computer tomography lung images using Echo State Neural Networks, Journal of Theoretical and Applied Information Technology, 68 (3), (2014) pp. 504-513.
- 11. Lukosevicius, M., Jaeger, H., Reservoir computing approaches to recurrent neural network training, Computer Science Review, vol. 3, pp. 127–149 (2009)
- 12. Meftah, B., Lézoray, O., Benyettou, A., Novel Approach Using Echo State Networks for Microscopic Cellular Image Segmentation, Cognitive ComputationVolume 8, Issue 2, 1 April 2016, pp. 237-245
- Nidhi, M. T., Gunaseelan, K., Examining the variation of vascular structure in digital fundus images using textural pattern, Personal and Ubiquitous Computing, 22 (5-6), pp. 961-970 (2018)
- 14. Nidhi, M.T., Gunaseelan, K., Efficient ranking of diabetic retinopathy and glaucoma using echo state neural network and radial basis function (RBF), Journal of Medical Imaging and Health Informatics, 6 (3), (2016) pp. 869-874.
- Otsu, N., A threshold selection method from gray-level histograms, IEEE Trans. on SMC, 9 (1) (1979) pp. 62-66.
- Schrauwen, B., Wandermann, M., Verstraeten, D., Steil, J.J., Stroobandt, D., Improving reservoirs using intrinsic plasticity, Neurocomputing, vol. 71, pp. 1159–1171 (2008)
- 17. Souahlia, A., Belatreche, A., Benyettou, A., Ahmed-Foitih, Z., Benkhelifa, E., Curran, K., Echo state network-based feature extraction for efficient color image segmentation, Concurrency Computation, 32 (21), art. no. e5719, (2020)
- Souahlia, A., Belatreche, A., Benyettou, A., Curran, K., Blood vessel segmentation in retinal images using echo state networks, 9th International Conference on Advanced Computational Intelligence, ICACI 2017, pp. 91-98 (2017)
- Souahlia, A., Belatreche, A., Benyettou, A., Curran, K., An experimental evaluation of echo state network for colour image segmentation, Proceedings of the International Joint Conference on Neural Networks, 2016-October, pp. 1143-1150 (2016).
- Steil, J.J., Online reservoir adaptation by intrinsic plasticity for back-propagationdecoleration and echo state learning, Neural Networks, vol. 20, pp. 353–364 (2007)
- Yager, R., Filev, D., Generation of fuzzy rules by mountain clustering, Journal of Intelligent and Fuzzy Systems, 2 (3) (1994), pp. 209-219.