# Optoelectronic reservoir computer for early stage alzheimer's disease detection

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**Nickson Mwamsojo [1], Frederic Lehmann[2], Mounim A. El−Yacoubi[1], Kamel Merghem[1], Yann Frignac[3], Badr-Eddine Benkelfat[1], and Anne-Sophie Rigaud[4]**

[1] *Electronics and Physics Department, Telecom Sudparis, 19 place Marguerite Perey, 91120 Palaiseau, France*
[2] *Communications, Images and Information Processing Department, Telecom Sudparis, 19 place Marguerite Perey, 91120 Palaiseau, France*
[3] *Huawei Technologies France, 18 Quai du Point du Jour, 92100 Boulogne-Billancourt, France*
[4] *AP-HP, Groupe Hospitalier Cochin Paris Centre, Hôpital Broca, Pôle Gérontologie, Paris, France*

**Abstract:** An optoelectronic Reservoir Computer is proposed and implemented numerically and on physical hardware for early-stage Alzheimer's disease detection for the first time. The approach yields classification accuracy of 85% surpassing state-of-the-art performances. 

## 1. Introduction

Alzheimer's is a brain disease associated with decline in patients' ability to think, recall and analyze information so as to be functioning members in the society. The disease is prevalent among the senior members of the population causing dependency [1]. Early Stage Alzheimer's Disease detection (ES-AD) is crucial since the efficiency of the drugs that slow the progression of the disease relies on extent of the disease.

Alzheimer's disease impacts the patients ability to control fine movements hence the disease manifests itself in the patients' handwriting (HW). Knowing this, previous works employ Machine Learning-based classification techniques such as Linear Discriminant Analysis (LDA) [3] to classify the Alzheimer's Patients (AP) from the Healthy Patients (HP) from HW features. These works, however, assume that there is a unique pattern in the HW discriminatory for the disease, an assumption contested by the authors of [4] whose results proved that exploring the full HW dynamics is beneficial for detection.

The ES-AD task, like most pattern recognition and time series prediction tasks are difficult to solve in an algorithmic manner but can be solved using Artificial Neural Networks (ANNs). The high complexity of traditional ANNs (i.e. large number of trainable parameters), however, makes them prone to over-fitting in applications with small number of training samples. We propose using Reservoir Computing (RC) to process the full HW dynamics as a time series for the ES-AD classification task. RC is a highly recurrent yet low complexity class of Recurrent Neural Networks (RNNs) making it suitable for processing serial tasks with small datasets like the HW data in this case. We also show that, RCs' hardware feasibility and versatility can be leveraged for hardware RC setups by implementing an opto-electronic setup optimized for this task of practical importance.

## 2. The proposed model and the classification setup

Reservoir computing was introduced by the authors of [5]. RCs have an attractive trait of allowing hardware implementations of complex neuronal networks which would otherwise not be physically feasible. They typically have three layers as shown in Fig. 1 (a). The first layer, the input layer, randomly projects the input information and then sends it to drive the second layer known as the reservoir layer. The reservoir layer is a complex network of randomly connected neurons that yield transients when driven by the input. These transient states represent computation i.e. the projection of the input into a higher dimensional space. The third layer, the only layer that is trained unlike other classes of RNNs, captures these transient states and maps them to the expected labels by a simple linear regression. The randomness of the reservoir layer and simplified training in the output layer encouraged hardware implementations using off-the-shelf telecommunication equipments such as in [6].

We begin by implementing numerically the delay-based RC achitecture from [6] and optimize it. We call this the digital RC to distinguish it from the subsequent equivalent hardware implementation. Then we proceed to implement the equivalent optoelectronic hardware RC and optimize it for the ES-AD task.

The dataset for ES-AD consists of 54 patients, 27 of whom are HP and 27 are AP. Each patient drew on a tablet four sets of four cursive- $\ell\ell\ell\ell$ letters to form a pattern shown in Fig. 1 (b). The HW data is preprocessed to obtain individual loops giving in total 866 loops [7]. Using stratified sampling technique we split the patients' data into $\frac{7}{9}$ for training, $\frac{1}{9}$ for validation and $\frac{1}{9}$ for testing. We report the test classification metrics obtained by maximum voting on individual loop predictions and compare it to the state-of-the-art results of the k-Medoid approach in [7].

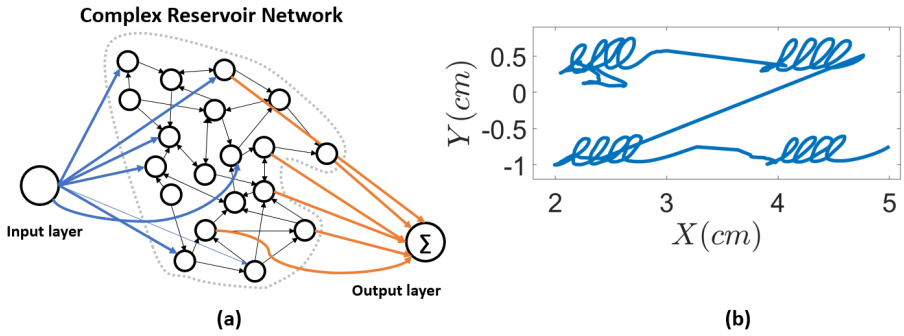


Fig. 1. (a) Basic RC architecture (b) Example of patients cursive-$\ell\ell\ell\ell$ entry

## 3. Results

After hyperparameters optimization for both the digital RC and the hardware RC using nested cross-validation technique we obtain classification perfomances reported in Table 1 where : Accuracy (**Acc**) is the percentage of correctly classified individuals, Sensitivity (**Sens**) is the percentage of correctly classified APs and Specificity (**Spec**) is the percentage of correctly classified HPs. The digital RC yielded the detection accuracy of 85% while the equivalent optoelectronic setup yielded the accuracy of 83%.

Table 1. Performance metrics for the proposed models and the state-of-the-art

| **Implementation** | **Acc** (%) | **Sens** (%) | **Spec** (%) |
|---|---|---|---|
| Digital | 85 | 88 | 83 |
| Hardware | 83 | 92 | 74 |
| k-Medoids [7] | 74 | 75.6 | 72.2 |

## 4. Conclusion

We demonstrate the advantage of low complexity of RC for processing tasks with small datasets. Our experiments explore both the numerical simulation and the optoelectronic hardware implementation of RC. Surpassing the state-of the-art, our digital implementation yielded the accuracy of 85% while that of hardware RC yielded 83%. The slightly lower performance for the hardware RC could be attributed to noisy nature and limited optimization of the optoelectronic implementation. Our RC implementation, being versatile, can be adapted for processing many other time series applications such as the speech recognition and non-linear channel equalization. In the future, we extend this work to quantify the gain in accuracy and costs efficiency of optimizing and training RCs compared to traditional more complex RNNs and consider improved hardware RC architectures for better accuracies.

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