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Preliminary Experimental Analysis of Reservoir Computing Approach for Balance Assessment

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Abstract. Evaluation of balance stability in elderly people is of prominent relevance in the field of health monitoring. Recently, the use of Wii Balance Board has been proposed as valid alternative to clinical balance tests, such as the widely used Berg Balance Scale (BBS) test, allowing to measure and analyze static features such as the duration or the speed of assessment of patients' center of pressure. In an innovative way, in this paper we propose to take into consideration the whole temporal information generated by the balance board, analyzing it by means of dynamical neural networks. In particular, using Recurrent Neural Networks implemented according to the Reservoir Computing paradigm, we propose to estimate the BBS score from the temporal data generated by the execution of one simple exercise on the balance board. Preliminary experimental assessments of the proposed approach on a real-world dataset show promising results.

Keywords: Reservoir Computing, Learning with Temporal Data, Balance Assessment

1 Introduction

A sedentary lifestyle is a risk factor for the development of many chronic illnesses. The common physiological aging causes a decrease of global functional abilities: one of the most important is balance disorder [16]. The control of balance is complex, with a strong integration and coordination of multiple body elements including visual, auditor and motor systems [9]. A comprehensive clinical assessment of balance is important for both diagnostic and therapeutic reasons in clinical practice [4, 17]. The Berg Balance Scale (BBS) test is considered the gold standard assessment of balance with small intra-inter rater feasibility and good internal validity. The work in [3] assessed the validity of the BBS by examining how scale scores are related to clinical judgments, laboratory measures of postural sway and external criteria reflecting balancing ability. Furthermore, scores could predict falls in the elderly, and how they are related to motor and functional performance in stroke patients. The Berg's utility includes grading different patients' balance abilities, monitoring functional balance over time and evaluating patients responses to different protocols of treatment [18]. Based on a test of 14 exercises/items, BBS is performance-based and has a scale of 0-4

(clinician assigned) score for each item, with a maximum overall score of 56. Within the scopes of the DOREMI European project (GA 611650), a technological platform to support and motivate older people to perform physical activity is under development, aiming at reducing sedentariness, cognitive decline and malnutrition, promoting an improvement of quality of life and social inclusion. One of the element of DOREMI platform is a smart carpet, based on the use of Nintendo Wii Balance Board (WBB), able to gather information pertaining to users' weight distribution at the four corners of the board. Such tool allows to design an automatic system for balance assessment through the daily repetition of one simple BBS exercise. This type of analysis, done by users at medical facilities or, remotely, at their own houses, can help clinicians in the evaluation of older people equilibrium and in control of its evolution.
The use of the WBB is motivated by the fact that it represents a low-cost and portable tool, recently successfully adopted for problems related to standing posture correction [14] and for training standing balance in the elderly [19]. Interestingly, the WBB has been validated in comparison with gold standard force platforms [13] in its reliability to track users' balance parameters, such as the center of pressure path length and velocity [5]. However, it is worth to observe that the whole signal time-series generated by the WBB potentially contains a richer information than such static parameters. Thereby, in this paper we propose to analyze the data generated by WBB using Recurrent Neural Networks (RNNs), which are learning models suitable for catching and processing dynamic knowledge from noisy temporal information. In particular, we considered the problem of estimating the BSS score of a patient using in input the temporal information generated by the execution of one simple BBS exercise on the WBB. This approach potentially allows to avoid the need to repeat all the 14 BBS exercises for new patients. An alternative approach in [15] tries to estimate the BBS score of a patient using information extracted from a tri-axial accelerometer placed on the lower back during the execution of some items of the BBS. Such approach, however, adopts a solution which is more intrusive for the patient. At the best of our knowledge, our work represents the first attempt at estimating the BBS score directly from the temporal data generated while the patient performs a simple balance exercise in an non-intrusive way using an external device.

2 Balance Assessment with RC

A measurement campaign has been conducted on 21 volunteers, aged between 65 and 80 years. We measured the weight signal produced by the WBB at the 4 corners of the board sampled at 5 Hz during the execution of the exercise # 10 in the BBS test, i.e. *turn to look behind*, selected for its simple execution and short duration ($\approx$ 10 seconds). To take into account for possible variations in the exercise executions, for each patient we recorded data from a number of maximum 10 repetitions of the exercise. We therefore obtained a *Balance dataset* for a regression task on sequences, containing couples of the type $(\mathbf{s}, y_{tg})$, where $\mathbf{s}$ is the 4-dimensional input sequence of users' weight values recorded by the WBB

during the exercise and y_{tg} is the target BBS score (over all the 14 exercises) of the corresponding patient, representing the ground-truth evaluated by a clinician during the campaign. For performance assessment we adopted the Mean Absolute Error (MAE) of the BBS score estimation provided by the learning models. It is worth noticing that the Balance dataset contains an outlier patient with BBS score of 24, which has been discarded for performance evaluation.
We model the dynamics of the temporal data involved by the balance evaluation task by dynamical neural networks models within the class of RNNs. In particular, we adopt the Reservoir Computing (RC) approach [12] for RNN modeling, and take into consideration the Leaky Integration Echo State Network (LI-ESN) [11, 10], a state-of-the-art model for efficient learning in sequential/temporal domains, which has proved to be particularly suitable in dealing with the nature of the input data originated from sensors [1, 2]. LI-ESNs implement discrete time dynamical systems, and consist of two main components, a dynamical reservoir, which realizes a recurrent encoding of the input history and provides the system with a memory of the past [6], and a static readout which computes the output. A LI-ESN is composed of an input layer with N_U units, a recurrent non-linear reservoir layer with N_R sparsely connected units, and a linear readout layer with N_Y units. At each time step t, the reservoir computes a state $\mathbf{x}(t) \in \mathbb{R}^{N_R}$ according to a state transition function $\mathbf{x}(t) = (1-a)\mathbf{x}(t-1)+a\tanh(\mathbf{W}_{in}\mathbf{u}(t)+\hat{\mathbf{W}}\mathbf{x}(t-1))$, where $\mathbf{u}(t) \in \mathbb{R}^{N_U}$ is the input at time step t, $\mathbf{W}_{in} \in \mathbb{R}^{N_R \times N_U}$ is the input-to-reservoir weight matrix, $\hat{\mathbf{W}} \in \mathbb{R}^{N_R \times N_R}$ is the recurrent reservoir weight matrix, and $a \in [0, 1]$ is the leaking rate parameter that controls the speed of the reservoir dynamics [11, 12]. For sequence-to-element regression tasks in which an output value is required in correspondence of an entire input sequence, the use of a mean state mapping function has proved to be effective [7, 8]. Accordingly, given an input sequence of length n, $\mathbf{s} = [\mathbf{u}(1), \ldots, \mathbf{u}(n)]$, we average the state activation over the steps of the input sequence, i.e. $\chi(\mathbf{s}) = \frac{1}{n}\sum_{t=1}^{n}\mathbf{x}(t)$. Then, the readout is applied to compute the output of the model $\mathbf{y}(\mathbf{s}) \in \mathbb{R}^{N_Y}$ by a linear combination of the elements in $\chi(\mathbf{s})$, i.e. $\mathbf{y}(\mathbf{s}) = \mathbf{W}_{out}\chi(\mathbf{s})$, where $\mathbf{W}_{out} \in \mathbb{R}^{N_Y \times N_R}$ is the readout-to-reservoir weight matrix. The readout is the only LI-ESN component that is trained, typically by efficient linear methods, e.g. pseudo-inversion and ridge regression [12]. The reservoir is left untrained after initialization under the constraints of the *echo state property* (ESP) [10, 12, 6]. A reservoir initialization condition related to the spectral radius of $\hat{\mathbf{W}}$ is often used in literature and is adopted in this paper, i.e. $\rho((1-a)\mathbf{I} + a\hat{\mathbf{W}})) < 1$ (see e.g. [12, 6] for details).

3 Experimental Results

The experimental analysis presented in this paper aimed at preliminarily assessing the generalization performance of the proposed RC approach. At the same time, in order to reduce the patients' effort for future data gathering campaigns, we were also interested in empirically analyzing the trade-off between the number of exercise repetitions for each patient required for training and the predictive performance that can be achieved. Accordingly, we took into consideration two

experimental settings. In the first experimental setting, the Balance dataset was split in a training set, containing data from 17 patients ($\approx 80\%$ of the total), and an external test set for performance assessment, containing data from 4 patients ($\approx 20\%$ of the total, chosen in order to represent a uniform sampling in the range of possible BBS target values). We considered LI-ESNs with reservoir dimension in $N_R \in \{100, 200, 500\}$, 10% of reservoir units connectivity, leaky parameter $a \in \{0.1, 0.3, 0.5, 0.7, 1\}$ and spectral radius $\rho = 0.99$. For each reservoir hyper-parametrization, we independently generated 5 reservoir guesses, averaging the results over such guesses. For readout training we used pseudo-inversion and ridge regression with regularization $\lambda_r \in \{10, 1, 0.7, 0.5, 0.3, 0.1, 0.01, 0.001\}$. The values of the reservoir hyper-parameters and readout regularization were chosen by model selection, adopting a 4-fold cross validation scheme over the training set. The selected LI-ESN resulted in a very good predictive performance, with a test MAE of 4.25 ± 0.39, which outperforms the results in [15] for patients within a corresponding age range. Such results appear promising, also considering the tolerance in the ground-truth data due to human observations. Moreover, we observed that the test error is higher for patients with lower BBS target scores, which correspond to a less sampled region in the input space.
We also conducted a preliminary empirical investigation in order to evaluate how the performance of the proposed LI-ESN approach scales with the number of available training data for each patient. Accordingly, we uniformly split the Balance dataset into groups containing sequences pertaining to 3 patients each, according to a 7-fold cross validation scheme, progressively reducing the number of training sequences for each patient. For this second experimental setting, we restricted to the case of LI-ESNs with $N_R = 100$ reservoir units, whereas all the others reservoir hyper-parameters and readout regularization values were selected (for each fold) on the validation set, considering the same range of values as in the case of the first experimental setting. Fig. 1 shows the MAE achieved by LI-ESNs on the validation set, for decreasing number of available training sequences. Results show that the validation performance is approximately stable for a number of training sequences per patient in the range of 10-4, while it gets rapidly worse as less than 4 training sequences per patient are used.

4 Conclusions

We have proposed an approach for assessing the balance abilities of elderly people based on RC networks, used for temporal processing of data recorded by a WBB during the execution of a simple BBS exercise, with the major advantage of automatically evaluating the BBS score using only 1 of the 14 exercises. The preliminary experimental analysis on a real-world dataset showed that our approach is able to achieve a very good predictive performance, up to ≈ 4 points of discrepancy in the BBS score with respect to the gold standard, which is good also considering both the use of a single BBS item and the tolerance typical of any subjective assessment scale. Overall, the possibility to infer the BBS scores with a good performance starting from the signal of a single BBS exercise shows

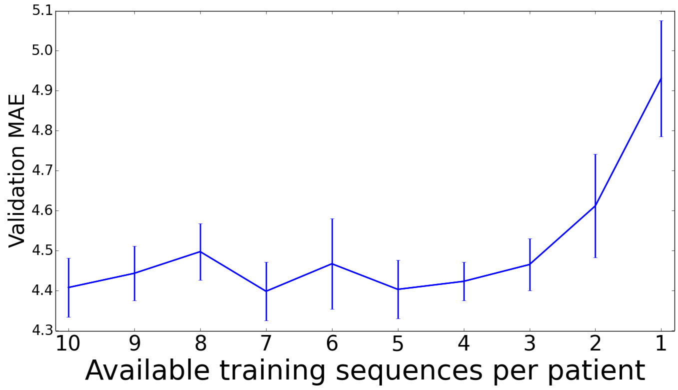

Fig. 1. Validation MAE (and standard deviation) achieved by LI-ESNs on the Balance dataset for a decreasing number of training sequences available for each patient.

the potentiality of our idea of exploiting the entire curve of the signal stream as a rich source of information for the evaluation of balance assessment. We also addressed the problem of evaluating the trade-off between the predictive performance and the number of exercise repetitions required for training the RC networks. A moderate number of repetitions in the training set turned out to be already sufficient for achieving a good performance. This aspect is of particular interest in view of minimizing the effort required for the collection of an adequate and sufficiently sampled dataset for balance estimation, as the repeated execution of BBS exercises by elderly people could be onerous. The results illustrated in this preliminary study have a potential utility by themselves, for the development of a balance estimation tool, and they will be eventually exploited within the purposes of the DOREMI project as a part of a larger health monitoring system aiming at improving elderly quality of life and active aging.

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