Gait Analysis of Autistic Children with Echo-State Networks

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This work addresses the problem of classification of multi-modal time-dependent signals, namely the gait motion of autistic and normal children, using the reservoir-based paradigm of Echo-State Networks.

Introduction. Many studies suggest that human movements are controlled and organized not as a reaction but as a goal driven action, and that this is already noticeable in newborn children [1, 2]. Neurodevelopment disorders such as autism have an effect on several aspects of motor control [3, 4, 5]. Here we will focus on the analysis of gait patterns between autistic and normal children, starting from the observation that statistical analysis shows a variance in some features of their walk cycle (step length, waist bobbing) [6]. We treat the walk cycle as a dynamic pattern and try to extract the information that shows a relevant difference between normal and autistic children by exploiting the temporal correlations across the joints involved in the gait motion. This research aims at deciphering some of the aspects of the child motion control and the way autism may affect it.

Classification Methods. Reservoir-based Recurrent Neural Networks (RNN) are an efficient way of analysing dynamic patterns while avoiding the complex and computationally intensive training procedures of standard RNN models. In this work, we used the Echo-State Network (ESN) [7] paradigm to analyze and classify our motion data[1]. The dynamic reservoir is able to contain and represent the temporal relations and dependencies of the input data and a single layer of output units gathers that information for classification. The training consists solely in selecting from the output units the elements that contribute to classification via a linear regression. Compared to other state-of-the-art systems such as Hidden Markov Models (HMM) the Echo-State Network offer a greater biological plausibility (this is truer yet for LSM, which are based on biologically modeled spiking neurons) and a significantly simpler and faster training (ESNs have been trained for some problems more than forty times faster than HMMs [9]). However, the readability of the internal states is still quite obscure in ESN and LSM, while it is easier to extract a number of informations from the internal features of HMMs.

Figure 1: Positions of the motion-capture markers for gait analysis.

Implementation and Results. A set of walk cycles from autistic and normal children recorded following the guidelines of [10] was used for input[2]. The data format is a collection of 3d coordinates from 14 markers applied to the joints of the lower body of the child (Fig. 1). The data was normalized by the height of the child. A reservoir of 200 sigmoid units was used to collect the data and 2 sigmoid units were used as output (Fig. 2). The internal weights as well as the input weights of the reservoir are randomly generated. Preliminary tests showed that the performance using feedback connections from the output units to the reservoir was significantly reduced, hence no feedback connection was used.

Tests were made on the length of the input cycle (i.e. only part of the full walk cycle was used). For the best input length found (Fig. 3), an offset was tried to find the most significant portion of the walk cycle. While the best performance was obtained with the full walk cycle, comparable results were obtained using only half a cycle. Tests were made on subsets of the input markers, dividing them into shoulders, waist and legs. PCA was also applied using different amounts of principal components (Fig. 4). The results are seen in Table

[1] testing with the closely related Liquid-State Machines (LSM) [8] is planned for future works

[2] The actual data is under Non Disclosure Agreement, and thus no representation of the inputs will be possible.

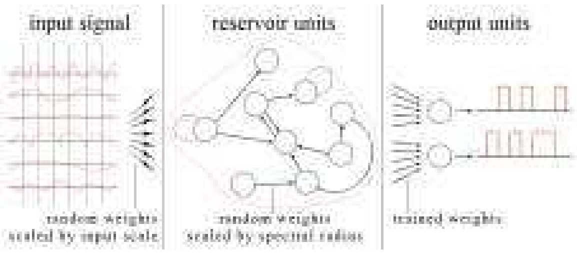

Figure 2: Schema of the Echo-State Network, the system is feed-forward, with no feedback connections from the output units to the reservoir and with no inputs entering directly into the output units. The internal recurrent connections are randomly generated.

1. Following the trend of most experiments on ESN, the three parameters of connectivity, spectral radius of the reservoir units and input scaling were trained on the best cycle length and offset found with the previous tests. The connectivity does not seem to have a significant impact on the performance. Changing the spectral radius seems to affect only slightly the performances, with results somewhat improved with radii greather than 1.0. The input scaling is the only parameter that shows a difference in the resulting performance (Fig. 5).

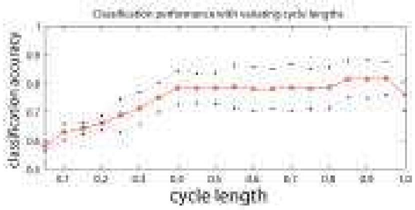

Figure 3: Classification performance with different fractions of the walk cycle. Usually the length of a full walk cycle (from the beginning of the left foot stance period to the end of the left foot swing period) is of 100 frames. The performance does not show dramatic improvements using more than 40% of the full walk cycle.

Subset	*Inputs*	*Performance*
Legs only	18	0.78 ± 0.12
Waist + Shoulders	24	0.80 ± 0.12
Legs + Shoulders	27	0.83 ± 0.12
Legs + Waist	33	0.80 ± 0.12
Full	42	0.85 ± 0.11
PCA-15	15	0.86 ± 0.12
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ICA-13	13	0.72 ± 0.13

Table 1: Results of testing using different subparts

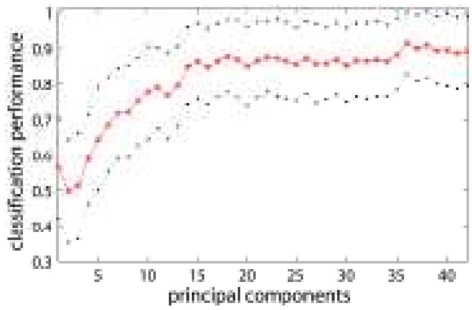
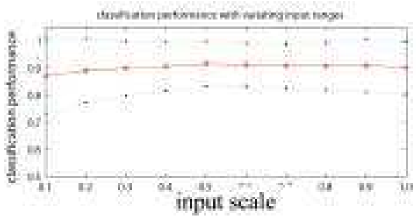


Figure 4: Average performance of the classifier using increasing number of principal components.



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References

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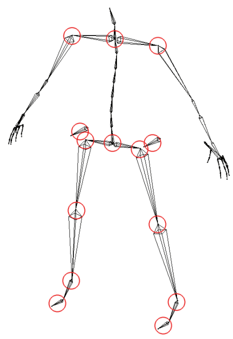

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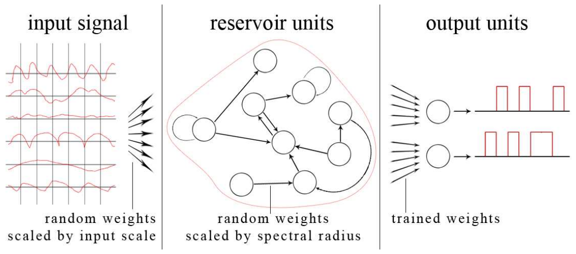

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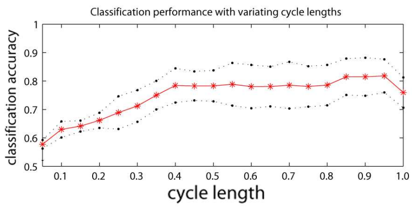

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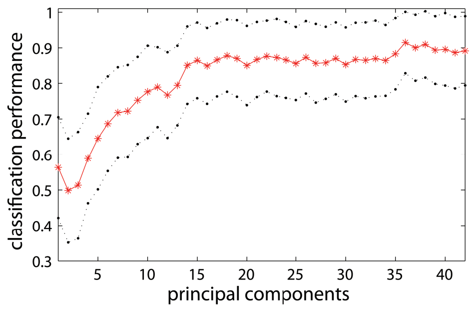

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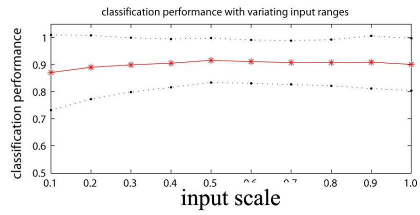

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