Abstract—Dyslexia is a neurodevelopmental learning disorder that affects the acceleration and precision of word recognition, therefore obstructing the reading fluency, as well as text comprehension. Although it is not an oculomotor disease, readers with dyslexia have shown different eye movements than typically developing subjects during text reading. The majority of existing screening techniques for dyslexia’s detection employ features associated with the aberrant visual scanning of reading text seen in dyslexia, whilst ignoring completely the behavior of the underlying data generating dynamical system. To address this problem, this work proposes a novel self-tuned architecture for feature extraction by modeling directly the inherent dynamics of wearable sensor data in higher-dimensional phase spaces via multidimensional recurrence quantification analysis (RQA) based on state matrices. Experimental evaluation on real data demonstrates the improved recognition accuracy of our method when compared against its state-of-the-art vector-based RQA counterparts.

Index Terms—Dyslexia screening, multidimensional recurrence quantification analysis, non-linear data analysis, wearable sensors

I. INTRODUCTION

Dyslexia is a neurodevelopmental learning disability that adversely affects between 5-10% of the population [1]. Specifically, it affects the way information is processed, stored and retrieved, with problems of memory, speed of processing, time perception, organization and sequencing [2]. Early-age identification and diagnosis of dyslexia is imperative in order to provide the necessary assistance to dyslexic candidates, since, as individuals grow older, compensatory mechanisms develop that help alleviate the symptoms of dyslexia [3]. However, the learning gap that has been developed is followed by poor school performance, causing psychological and emotional distress, low self-esteem, lack of motivation and depression [4], [5].

Although dyslexia is not a primary oculomotor disease, eye movements differ during reading between typical and dyslexic readers [6], [7]. Typically, in readers with dyslexia, fixation duration and number of fixations increase, average saccade length gets shorter and the number of regressions (i.e., short backward eye movements targeting text that has already been read) increases [8], [9]. The observed differences can be attributed to abnormal linguistic or cognitive processing [10].

The majority of existing screening techniques for dyslexia’s detection employ features associated with the aberrant visual scanning of reading text seen in dyslexia [1], [11] whereas there is also a report where the one-dimensional counterpart of RQA [12] is employed by [13] on dyslexia’s data for investigating dyslexic and non-dyslexic word-naming performance in beginning readers. Although such methods can lead to high-precision results in the one-dimensional case for relatively smooth data, they lack the capability of concurrently processing multiple dimensions. To overcome these limitations, this work proposes an alternative approach for accurate dyslexia detection, which exploits the temporal variability of the underlying dynamical system that generates the data. To this end, an extension of the multidimensional recurrence quantification analysis (mdRQA) framework [14] is proposed to perform a sophisticated non-linear analysis of multiple sensor streams. An mdRQA-based approach is able to treat non-stationary and short data series. Furthermore, it comprises a set of appropriate quantitative measures for the quantification of recurrent, typically small-scale, structures, and the detection of critical transitions in the systems dynamics (e.g. deterministic, stochastic, random). Finally, it is significant to mention that there is no recordings in the literature combining mdRQA on dyslexia data.

The contributions of our work are the following:

(i) the underlying multidimensional data generating processes are modeled concurrently and directly in a higher-dimensional phase space identifying more accurately the time-evolving dynamics of sensor streams;
(ii) our proposed method models the correlations not only within a stream but also between different streams;
(iii) an efficient feature extraction scheme is designed for the discovery of information-rich patterns that best capture the underlying data dynamics;
(iv) a totally self-tuned architecture is designed for unsupervised dyslexia’s detection.

The rest of the paper is organized as follows: In Section II, the dataset employed by our study is overviewed. Section III analyzes our proposed multidimensional RQA framework, based on state matrices, for feature extraction. Section IV evaluates the performance of our method and compares its accuracy with its vector-based mdRQA counterpart. Finally, Section V summarizes the main outcomes of this work and
gives directions for future extensions.

II. DATASET DESCRIPTION

The dataset provided by [1] consists of a sample of 97 (76 males and 21 females) high-risk subjects with early identified word decoding difficulties and a control group of 88 (69 males and 19 females) low-risk subjects. These subjects were selected from a larger population of 2165 school children attending second grade (age 8-9). Eye movement recordings made while the subjects were reading a short natural passage at 100 Hz. All subjects read one and the same text presented on a single page of white paper with high contrast. The text was distributed over 8 lines and consisted of 10 sentences with an average length of 4.6 words.

III. PROPOSED ARCHITECTURE

The vector-based mdRQA [14] extracts the underlying dynamics of an ensemble of recorded data streams by mapping the time series in a higher-dimensional phase space of trajectories. More specifically, given a multidimensional time series of length $N$ we reconstruct the corresponding phase space representation as follows,

$$
\begin{pmatrix}
    v_1 \\
    v_2 \\
    \vdots \\
    v_{N_s}
\end{pmatrix} =
\begin{pmatrix}
    x_{1,1} & x_{2,1} & \cdots & x_{D,1} \\
    x_{1,2} & x_{2,2} & \cdots & x_{D,2} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{1,N_s} & x_{2,N_s} & \cdots & x_{D,N_s}
\end{pmatrix}
$$

(1)

where $D$ is the number of dimensions of the streams’ ensemble, $x_{i,j} = (r_j, r_{j+1}, \ldots, r_{j+(m-1)\tau})$, $i = 1, \ldots, D$, $j = 1, \ldots, N_s$, with $m$ being the embedding dimension, $\tau$ the delay and $N_s = N - (m-1)\tau$ the number of states.

Recurrence plots (RPs) [12] have been proposed as an advanced graphical technique of visual nonlinear data analysis, which reveals all the times of recurrences, that is, when the phase space trajectory of the dynamical system visits roughly the same area in the phase space. Therefore, we define the multidimensional recurrence plot (mdRP) as,

$$
\text{mdR}_{i,j} = \Theta (\varepsilon - \|v_i - v_j\|_p), \quad i, j = 1, \ldots, N_s
$$

(2)

where $v_i$, $v_j$ denote the state vectors, $\varepsilon$ is a threshold, $\| \cdot \|_p$ denotes a general $\ell_p$ norm, $d$ is a distance metric and $\Theta(\cdot)$ is the Heaviside step function, whose discrete form is defined by,

$$
\Theta(n) = \begin{cases} 
1, & \text{if } n \geq 0 \\
0, & \text{if } n < 0 
\end{cases}, \quad n \in \mathbb{R}. 
$$

(3)

The disadvantage of the conventional mdRQA is that it does not capture the correlations between the distinct streams. To address this limitation, our proposed framework relies on state matrices instead of state vectors, to represent the time-delay embedding of a streams’ ensemble. Specifically, we define a state matrix $X_i$ as follows,

$$
X_i = \begin{pmatrix}
    x_{1,i} & x_{2,i} & \cdots & x_{k,i} \\
    x_{k+1,i} & x_{k+2,i} & \cdots & x_{2k,i} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{(l-1)k+1,i} & x_{(l-1)k+2,i} & \cdots & x_{lk,i}
\end{pmatrix}
$$

(4)

where $i = 1, \ldots, N_s$, $k = \lceil \sqrt{D} \rceil$ and $l = \lfloor D/k \rfloor$.

In the herein implementation, the optimal time delay $\tau$ is estimated as the first minimum of the average mutual information (AMI) function averaged over all the dimensions in the data [15]. Concerning the embedding dimension $m$, a minimal sufficient value is estimated using the method of false nearest neighbours (FNN) [16]. Finally, threshold $\varepsilon$ is chosen as the 15th percentile of the distance distribution of states [17].

Subsequently, the associated multidimensional recurrence plot (mdRP) is defined by

$$
\text{mdR}_{i,j} = \Theta (\varepsilon - d(M(X_i), M(X_j)))
$$

(5)

where $\varepsilon$ is a threshold, $M$ is an operator, $d$ refers to a distance metric and $\Theta(\cdot)$ is the Heaviside step function whose discrete form is defined by Eq. (3).

A major advantage of mdRPs is that they can also be applied to rather short and even nonstationary data. The visual interpretation of RPs, which is often difficult and subjective, is enhanced by means of several numerical measures for the quantification of the structure and complexity of multidimensional RPs. The following ten measures are utilized to form our feature matrix (ref. [18] for the definitions): recurrence rate, determinism, average diagonal/vertical length, length of longest diagonal/vertical line, entropy of diagonal/vertical length, lamination and trapping time. Finally, a linear-kernel support vector machine (SVM) is applied on the feature matrix for activity recognition. Fig. 1 shows the overall architecture of our proposed mdRQA-based dyslexia’s detection system.
IV. PERFORMANCE EVALUATION

A. Distance Metrics and Operators

1) Vector-based mdRQA: The choice of the $\ell_p$ norm depends on the nature of the data. The most commonly used norms include the (i) Euclidean norm, (ii) maximum norm and (iii) minimum norm. Our extensive evaluation on real data showed that the Euclidean norm performs best for the specific type of dyslexia’s data.

2) Proposed matrix-based mdRQA: Given the two-dimensional nature of our state matrices, appropriate distance metrics $d$ must be defined for our proposed mdRQA method. Specifically, the following distance metrics and matrix operators are utilized and tested for the construction of mdRPs:

- **Euclidean norm of state matrix eigenvalues:** Setting the operator $\mathcal{M}$ to be the calculation of the eigenvalues vector of a state matrix using the singular value decomposition (SVD) [19], Eq. (5) takes the following form,

  $$
  \text{mdR}_{i,j} = \Theta \left( \varepsilon - \| x_{eig}^i - x_{eig}^j \|_2 \right) \tag{6}
  $$

  where $x_{eig}^i$ and $x_{eig}^j$ are the eigenvalues vectors of the state matrices $X_i$ and $X_j$, respectively, $i, j = 1, \ldots, N_i$, $\varepsilon$ is a threshold and $\Theta(\cdot)$ is the Heaviside step function given by Eq. (3).

- **Correlation matrix distance:** In order to measure the change of spatial second-order statistics, the correlation matrix distance (CMD) [20] between correlation matrices is employed, which is defined by

  $$
  d(C_i, C_j) = 1 - \frac{tr\{C_i C_j\}}{||C_i||_F ||C_j||_F} \in [0, 1] \tag{7}
  $$

  where $C_i$ and $C_j$ are the correlation matrices of the state matrices $X_i$ and $X_j$, respectively, $tr\{\cdot\}$ is the trace operator and $||\cdot||_F$ denotes the Frobenius norm. The CMD becomes zero if the correlation matrices are equal up to a scaling factor and one if they differ to a maximum extent. The more the signal spaces of $C_i$ and $C_j$ overlap, the higher becomes the trace of the product and therefore the CMD decreases. This property of CMD makes it a useful measure to evaluate whether the spatial structure of the signal, hence, the signal statistics have changed to a significant amount.

  Subsequently, the associated mdRP is defined by,

  $$
  \text{mdR}_{i,j} = \Theta \left( \varepsilon - d(C_i, C_j) \right) \tag{8}
  $$

  where $d$ is the correlation matrix distance, $\varepsilon$ is a threshold and $\Theta(\cdot)$ is the Heaviside step function.

**B. Classification**

The sensor data and metadata of each participant are concatenated and then divided randomly into training and testing subsets containing 70% and 30% of the data, respectively. A non-linear classifier, namely, a linear-kernel SVM, is applied on the generated feature matrix in order to perform dyslexia’s recognition, which is addressed as a classification problem. The classification procedure is repeated 100 times and the average is reported. The choice of this classifier is motivated by its fast execution, as well as by its high accuracy, especially in the case of a large number of available features. We emphasize, though, that the classification step is decoupled from the feature extraction step, thus the overall performance of the architecture can be further improved by employing a better classifier.

C. Evaluation Metrics

The performance of our matrix-based mdRQA architecture is compared against the vector-based mdRQA counterpart, in terms of classification accuracy and robustness to noise. Specifically, saccadic eye movement, which is a fast random convulsing movement even when the eye fixates on one point, can be modeled as white noise due to its randomness. Moreover, there is no preference to the direction of the eye movement, therefore we may claim that the governed eye movement model is approximated by an additive Gaussian noise process. Along these lines, we evaluate the robustness of our proposed method when Gaussian noise is added to the data with a signal-to-noise ratio (SNR) varying in $\{10, 20, 40\}$ dB.

**D. Evaluation Results**

Table I displays the classification accuracy averaged over 100 repetitions, for the previous vector-based mdRQA approach and our proposed method. As it can be seen, the
Euclidean distance between the state matrices eigenvalues outperforms the rest, in terms of classification accuracy. Precision and recall percentages for each architecture examined are provided in Table II. Precision expresses the percentage of the results which are relevant, while recall refers to the percentage of total relevant results correctly classified by each algorithm. Furthermore, Fig 2 depicts the averaged classification accuracy for SNR values of 10 dB, 20 dB and 40 dB, for each of the aforementioned architectures. Considering low SNR values, the correlation matrix distance outperforms the rest, whereas the vector-based mdRQA architecture has the lowest performance. On the other hand, in case of higher SNR values, the correlation matrix distance achieves the lowest score, which reveals the sensitivity of statistical measures to the underlying noise. In general, our results showed that the Euclidean distance between the eigenvalues vectors of state matrices provides the optimal performance in the presence of additive Gaussian noise.

V. CONCLUSIONS AND FUTURE WORK

In this work, we designed and implemented a fully self-tuned dyslexia detection architecture based on a representation of wearable sensor data in higher-dimensional phase spaces using mdRQA based on state matrices for capturing the underlying dynamics of the data. The experimental evaluation on real data revealed the superiority of our proposed framework, when compared against its vector-based counterpart, in terms of classification accuracy and robustness to noise. As a future work, we intend to investigate the use of alternative distance measures and operators tailored to state matrices, in order to better capture specific characteristics of the dynamical system under study. Furthermore, we will extend our matrix-based mdRQA to a more generic tensor-based framework, in order to model directly the inherent spatio-temporal dynamics of sensor streams.

REFERENCES