Psychiatric patient monitoring based on a dynamical recurrence analysis of multidimensional wearable sensor data

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ABSTRACT

Human activity recognition (HAR) is encountered in a plethora of applications such as pervasive health care systems. This work proposes a novel self-tuned HAR architecture for feature extraction and accurate recognition of certain leisure activities, by modeling directly the inherent dynamics of multidimensional wearable sensor data in higher-dimensional phase spaces. Results show that our method is able to detect target activities in a large data set with high precision and recall scores.

KEYWORDS

Human activity recognition, multidimensional recurrence quantification analysis, nonlinear data analysis, wearable sensors

1 INTRODUCTION

Psychiatric patient monitoring aims at characterizing both mood and behavioral trends by recording activity data over a period. Apart from daily activities such as sleep and food intake, patients might, for instance, stop a leisure activity when depressed, or vigorously practice for several hours in a manic episode [1]. To this end, we propose an alternative approach for accurate human activity recognition, which exploits the temporal variability of the underlying dynamical system that generates the data associated with a specific activity. Along these lines, multidimensional Recurrence Quantification Analysis (mdRQA) will be exploited to perform a sophisticated nonlinear analysis of sensor streams.

2 MULTIDIMENSIONAL RECURRENCE QUANTIFICATION ANALYSIS

Given a multidimensional time series of length N we reconstruct the corresponding phase space representation as,

$$\begin{pmatrix} \mathbf{v}_1 \\ \mathbf{v}_2 \\ \vdots \\ \mathbf{v}_{N_s} \end{pmatrix} = \begin{pmatrix} \mathbf{x}_{1,1} & \mathbf{x}_{2,1} & \cdots & \mathbf{x}_{D,1} \\ \mathbf{x}_{1,2} & \mathbf{x}_{2,2} & \cdots & \mathbf{x}_{D,2} \\ \vdots & \vdots & \ldots & \vdots \\ \mathbf{x}_{1,N_s} & \mathbf{x}_{2,N_s} & \cdots & \mathbf{x}_{D,N_s} \end{pmatrix} \tag{1}$$

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

In our proposed approach, each state vector $\mathbf{v}_i = (\mathbf{x}_{1,i}, \mathbf{x}_{2,i}, \ldots, \mathbf{x}_{D,i})$ is converted to a matrix $\mathbf{X}_i$ as follows,

$$\mathbf{X}_i = \begin{pmatrix} \mathbf{x}_{1,i} & \mathbf{x}_{2,i} & \cdots & \mathbf{x}_{k,i} \\ \mathbf{x}_{k+1,i} & \mathbf{x}_{k+2,i} & \cdots & \mathbf{x}_{2k,i} \\ \mathbf{x}_{2k+1,i} & \mathbf{x}_{2k+2,i} & \cdots & \mathbf{x}_{3k,i} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{x}_{(l-1)k+1,i} & \mathbf{x}_{(l-1)k+2,i} & \cdots & \mathbf{x}_{lk,i} \end{pmatrix} \tag{2}$$

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

The equivalent multidimensional Recurrence Plot (mdRP) can be defined as an array of points positioned at the places (i, j) in a square matrix such that,

$$\mathbf{R}_{i,j} = \Theta\left(\varepsilon - \|\mathbf{X}_i - \mathbf{X}_j\|_F\right), \quad i, j = 1, \ldots, N_s , \tag{3}$$

where $\mathbf{X}_i$, $\mathbf{X}_j$ are state matrices, ε is a threshold, $\| \cdot \|_F$ is the Frobenius norm and $\Theta(\cdot)$ is the Heaviside step function, whose discrete form is defined by

$$\Theta(n) = \begin{cases} 1, & \text{if } n \geq 0 \\ 0, & \text{if } n < 0 \end{cases} , \; n \in \mathbb{R} . \tag{4}$$

The threshold ε is chosen as a certain percentile of the distance distribution of states [2]. The resulting matrix $\mathbf{R}$ exhibits the main diagonal, $\mathbf{R}_{i,i} = 1$, $i = 1, \ldots, N_s$, also known as the *line of identity* (LOI). A major advantage of RPs 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 RPs [3]. The corresponding quantification measures are computed in small windows, which are then merged to form our feature matrix. Finally, a linear-kernel Support Vector Machine (SVM) is applied on the feature matrix for activity recognition.

3 CONCLUSIONS AND FUTURE WORK

In this work, we designed and implemented an automated HAR architecture based on a representation of multidimensional wearable sensor data in higher dimensional phase spaces using a novel multidimensional RQA method for capturing the underlying dynamics of the data. The experimental evaluation on real leisure data revealed the superiority of our multidimensional RQA-based framework in accurately monitoring mood disordered patients.

REFERENCES

[1] E. Berlin and K. Van Laerhoven. 2012. Detecting leisure activities with dense motif discovery. In *Proc. of the 2012 ACM Conf. on Ubiquitous Computing*. ACM, 250–259.
[2] K. H. Krämer, R. V. Donner, J. Heitzig, and N. Marwan. 2018. Dimension-scalable recurrence threshold estimation. *arXiv preprint arXiv:1802.01605* (2018).
[3] J. Zbilut and C. Webber. 1992. Embeddings and delays as derived from quantification of recurrence plots. *Phys. Lett. A* 171 (1992), 199–203.