Recurrence Analysis of Human Body Movements during Activities of Daily Living*

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Abstract—Recurrence quantification analysis (RQA) is used to differentiate and analyze the regular and irregular parts of a time-series signal using recurrence plots and quantification measures. This work presents RQA for human body movements during routine activities of daily life (ADL) using parameters recorded using a wearable sensor attached to the subject's waist. The current research uses data from 8 subjects performing 5 different daily life activities, lying and stand, pick and stand, sitting and stand, step up and down, and walking. Simulating the RQA plots for activity and non-activity phases for squared vector magnitude parameter for each of the record we quantify the level of signal stability and disruption in terms of RQA analysis measures recurrence rate (RR), determinism (DET) and line entropy (ENT). The RQA parameters reveal a chaotic behavior in case of activity (RR=0.249, DET=0.510, ENT=0.732), and a stable or least chaotic behavior in case of non-activity (RR=0.466, DET=0.726, ENT=1.205) regions of time. Distinguishing values for RQA-based measures for different human body movements taking place during daily life activities might be used for human activity monitoring, fall detection for elderly and body movement modelling and analysis algorithms.

Index Terms—recurrence quantification analysis, daily life activities, human body movements.

I. INTRODUCTION

One of the biggest challenges in the design and development of smart wearable devices targeted for 24 hour usage is catering for human body movements during daily life activities (ADL), in addition to low power consumption, on-chip processing, reducing interfering noises, fabrication material and user acceptance. Body movement modelling and analysis is a problem that needs to be addressed to enhance the functionality and usability of these sensing devices to put them to practical use [1]–[3].

Human body movements are analyzed for activity monitoring [4], fall detection for the elderly, technique analysis in athletes [5], dance composition [6], gait recognition, internet-of-things based healthcare sensors [7] and design and development of biomechanical products [8] etc.

Recurrence quantification analysis (RQA) [9], [10] has found recent popularity in the identification and quantification of synchronization patterns in dynamic and complex signals. This signal configuration can be characterized into time-varying regular and irregular system states. Recurrence plots have demonstrated to be a valuable data visualization and analysis tool for time-varying dynamical systems in a wide group of application areas for e.g. engineering [11], finance [12], biology [13], neuroscience [14], behavioral sciences [15], geosciences [16] and other disciplines.

Latest related work includes load-related movement complexity where Apley scratch, sit-and-reach and weight-bearing-lunge test were performed by subjects to quantify motion in the shoulders and thoracic spine, hip and trunk and dorsiflexion respectively [17]. Another research tests movement and cognition in a sit to stand task where adults executed a sit-to-stand task while counting backwards aloud as a secondary cognitive task [18]. Also, researchers analyzed posture maintenance of human test subjects on stable and stable sloped surfaces [19]. The current work is novel in terms of presenting a quantification analysis for everyday activities, hence is applicable to daily activity monitoring scenarios.

The currently selected database [20] offers a unique compilation of daily life activities and different types of falls performed by human subjects using a MARG sensor positioned at the subject’s waist. This work uses the ADL records for the analysis of human body movements only. RQA analysis has been performed using the squared vector magnitude for acceleration calculated using x, y and z-axis data. Each time-series record was divided into three equal sections to analyze the rest and activity states separately. Computing recurrence plots and quantification metrics: recurrence rate, determinism and entropy for the available activities: lying and standing, picking up something and standing, sitting and standing, stepping up and down and walking, we show the difference between movement and resting states.

The paper is organized as follows: Section-I overviews the technique of recurrence quantification and the motivation of applying it to human movement analysis. Section-II describes the mathematical formulation, simulation procedure and complexity measures based on recurrence plots. Section-III and IV report the results and provide a detailed discussion on the research outcomes plus mentions some possible future research directions. Section-V concludes the presented work.

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II. METHODOLOGY

A. Data Description

The data [20] was recorded with the help of 8 participants (6 males and 2 females) with average age 25.37 ± 2.56 years, height 1.79 ± 0.05 meters and weight 76.62 ± 10.59 kilograms. Duration of records is variable among different subjects, trials and activities. Data includes ADL: lying on a bed then standing, walking a few meters, sitting on a chair then standing, go up and down three steps and picking something up and then standing acquired using the MARG (Magnetic Angular Rate and Gravity) [1], a multi-sensory wearable device tied to the subjects waist.

The recorded data consists of parameters for each recording of which we made use of 5 parameters: time in seconds, acceleration along x, y and z-axis and squared vector magnitude measured in terms of gravitational acceleration g in meter per second square (1g = 9.80665 m/s²). Each record has three simultaneous acquisitions.

B. Mathematical Formulation

For a mathematical formulation of the recurrence analysis of body movements, we consider squared vector magnitude for acceleration $g_i(t)$, which for recording in number of samples can be written as $g_i(n)$ with $0 \leq n \leq N$ and $1 \leq i \leq 3$. Where, ‘i’ represents the number of equal sections $g(t)$ is divided in to analyze the occurrence of activity with respect to time and ‘N’ is the total number of samples in each signal.

Fig. 1 shows the signal recorded for 5 different activities. The figure shows the division of signal into 3 sections: Section-I, Section-II and Section-III. Also the figure labels activities occurring on the time series by visual inspection. Our aim here is to make the recurrence plots and calculate recurrence parameters for Section-I, II and III. Hence, for a single ‘g’ input record from the used database we get three recurrence matrices $r_1(t)$, $r_2(t)$ and $r_3(t)$, each calculated by eq. (1):

$$r_i = \begin{cases} 
1 & d(g_i, g_i) \leq \rho \\
0 & \text{else}
\end{cases}$$

where, ‘d’ is the distance metric, in the current case correlation $d(g_i, g_i) = \text{correlation}(g_i, g_i)$ and ‘$\rho$’ is the selected threshold used as a measure of closeness of points in the recurrence plot.

C. RQA Metrics

We present our analysis and results in terms of following recurrence quantification measures:

1) Recurrence Rate (RR): The recurrence rate corresponds with the probability that a specific state will recur and calculated as in eq. (2). High recurrence rates show a more periodic and less chaotic signal.

$$RR = \sum_{ij=1}^{N} r_i(\rho)$$

2) Determinism (DET): Determinism is the ratio of recurrence points that form diagonal structures (of at least length $l_{\text{min}}$ to all recurrence points and calculated as in eq. (3):

$$DET = \frac{\sum_{l=l_{\text{min}}}^{N} 1P(l)}{\sum_{l=1}^{N} 1P(l)}$$

3) Shannon Entropy (ENT): The Shannon entropy of the probability distribution of the diagonal line lengths $p(l)$ of $r_i(\rho)$ and measured by eq. (4):

$$ENT = - \sum_{l=l_{\text{min}}}^{N} p(l) \ln(p(l))$$

The value of threshold ‘$\rho$’ is different for multiple activities ranging between 0.1 and 0.4. Results are presented for 5 activities and 3 time stages as mean (standard deviation) over 24 records (8 subjects and 3 simulation runs). The significance of the results is tested using Lilliefors’s test setting $p < 0.05$. Total records processed are 120 (5 activities, 24 records for each activity).

III. RESULTS

Recurrence quantification measures, recurrence rate, determinism and entropy are calculated for the three sections of the recordings for ADL activities lying and then standing, picking up something and then standing, sitting and standing, stepping up and down, and walking for all recurrence matrices $r_1$, $r_2$ and $r_3$. Values for each section are reported in Table. I.

Average recurrence rates for section-I, II and III respectively for lying and standing are 0.869, 0.5 and 0.358, for picking and standing are 0.219, 0.242 and 0.319, for sitting and then standing are 0.380, 0.808 and 0.373, for stepping up and down...
are 0.166, 0.307 and 0.210, and for walking are 0.127, 0.118 and 0.137.

Average determinism for section-I, II and III respectively for lying and standing are 0.960, 0.799 and 0.777, for picking and standing are 0.491, 0.624 and 0.600, for sitting and then standing are 0.688, 0.948 and 0.756, for stepping up and down are 0.457, 0.616 and 0.476, and for walking are 0.339, 0.299 and 0.335.

Average entropy values for section-I, II and III respectively for lying and standing are 2.674, 1.398 and 1.226, for picking and standing are 0.635, 0.874 and 0.852, for sitting and then standing are 0.965, 2.061 and 1.120, for stepping up and down are 0.590, 0.863 and 0.634, and for walking are 0.430, 0.383 and 0.427.

By visual inspection of inputs in Fig. 1 and corresponding video files available with the dataset [20], section-I and section-II are non-activity and section-III is the activity phase for lying and then standing motion. Section-I and III are non-activity and section-II is the activity phase for picking and then standing motion. Section-I and II are non-activity and section-III is the activity phase for sitting and then standing motion. Section-II is the non-activity and section-I and III are the activity phase for stepping up and down motion. There is no visible difference between sections with respect to activity/non-activity in the walking action.

### IV. DISCUSSION

Understanding the changes between regular and irregular signal time periods in this case leads to identifying the rest and activity states of human body movements. As mentioned in the last paragraph, the observed mean values over the visually identified activity and non-activity sections respectively from Table. I for recurrence rate are 0.249 and 0.466, for determinism 0.510 and 0.726 and entropy are 0.732 and 1.205.

The highest recurrence is seen for the lying down phase and least for the walking activity showing that the signal is least disrupted while lying down and highly disrupted for walking activity. Determinism more or less follows the trend of recurrence. In other words, high value of determinism shows a less disrupted or rest phase in this case and low value shows a more disrupted or an activity state. High values of determinism are observed during the non-activity states and low values are reported during the activity performance states. High value of entropy is reported in the case of non-activity and low value is observed in case of activity states showing less signal information contained in the non-activity state and high information contained in the activity state.

Fig. 2 shows recurrence plots for all three time-divided sections I, II and III and, all five activities: a) lying and then standing, b) picking up something and standing, c) sitting and standing, d) stepping up and down and e) walking. These output recurrence plots correspond to the inputs shown in Fig. 1. The left column represents non-thresholded while the right column represents thresholded plots for all corresponding activities.

Fig. 2a identifies section-I as lying state, II as subject starting to move and III as the section in which the subjects position transitions from lying to standing position. Fig. 2b identifies section-I as subject starting to pick up state, II as subject main going down and moving back up activity and III as subject post-picking up section in which the subjects position transitions from moving up to standing position. Fig. 2c identifies section-I as sitting state, II as subject starting to move and III as the section in which the subjects position transitions from sitting to standing position. We notice similarities in section-III for both Fig. 2a and Fig. 2c (representing standing state in both cases) but differences in section-I between Fig. 2a and Fig. 2c (representing lying and sitting in the two referenced cases).

Fig. 2d identifies section-I as stepping up, II as subject resting for a moment and III as the section in which the subject steps down again. Fig. 2e identifies section-I, II and III as walking. We observe no clear difference between the three stages as the subject is continuously walking with a consistent body movement variation.

The differentiating RQA parameters for activity and non-activity phases can be used as novel classification parameters for machine learning algorithms for daily life activity monitoring and fall detection algorithms. The current study uses
only ADL records from the before-mentioned database.

The database also offers human fall detection records well-categorized in different types of human falls. The same analysis is intended to be performed in future for stratifying the record into pre-fall, fall and post-fall stages. The current work only uses one parameter SVM for recurrence analysis. Incorporating the phase records for pitch and roll angles into the record into pre-fall, fall and post-fall stages. The current analysis is intended to be performed in future for stratifying categorized in different types of human falls. The same analysis in this study, we used recurrence quantification analysis to depict human body movements during daily life activities for the assessment of activity using wearable sensing device. For all time-divided sections and every activity, the discriminating numerical values of RQA parameters recurrence rate, determinism and entropy show that RQA is a useful assessment method for quantitative modelling and analysis of human body movements for data acquired through novel multi-sensory wearable sensors.

V. CONCLUSION

In this study, we used recurrence quantification analysis to depict human body movements during daily life activities for the assessment of activity using wearable sensing device. For all time-divided sections and every activity, the discriminating numerical values of RQA parameters recurrence rate, determinism and entropy show that RQA is a useful assessment method for quantitative modelling and analysis of human body movements for data acquired through novel multi-sensory wearable sensors.

REFERENCES