Iranian Journal of Medical Physics
ijmp.mums.ac.ir

# The Impact of Gravitational Stress on Cardiac Dynamics Using Entropy

Atefeh Goshvarpour[1], Ateke Goshvarpour[2*]

1. Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran.
2. Department of Biomedical Engineering, Imam Reza International University, Mashhad, Razavi Khorasan, Iran.

ARTICLE INFO

*Article type:*
Original Paper

*Article history:*
Received: Mar 18, 2021
Accepted: Jul 10, 2022

*Keywords:*
Posture
Electrocardiography
Entropy
Classification
Nonlinear Dynamics

ABSTRACT

***Introduction:*** Until now, the gravitational stress effect on the time domain and frequency heart parameters has been well-documented. However, cardiac signal dynamics have not been studied adequately under the influence of postural changes. In addition, the effect of body positions on the bio-signals has been investigated only from the aspect of feature extraction and the classification problem has not been considered. Among the physiological signals, the heart rate (HR) becomes an emerging modality that captured the attention of many researchers due to its noninvasive recording and its ability to assess autonomic tone modulation. This study attempted to classify cardiac dynamics concerning postural changes by evaluating different entropy algorithms.

***Material and Methods:*** In this study, the ECG signals of 10 participants (five women and five men with a mean age of 28.7±1.2 years) were designated from the database available at Physionet. First, the RR-intervals of electrocardiograms complying with the Pan-Tomkins procedure were estimated. Second, several entropy measures, including Shannon, log energy, sample, differential, Tsallis, Renyi, and approximate entropy, were calculated while participants were in supine rest, in two rapid head-up tilts, two stand-ups, and two slow head-up tilts. Then, we applied the support vector machine to classify different postures using one group vs. all other remaining groups (OVA) and one body posture vs. the resting supine position (BVR) in a k-fold cross-validation scheme.

***Results:*** Empirical results showed that using the entropy measure in a BVR scheme leads to higher of accuracy rates up to 100%.

***Conclusion:*** This framework opens an avenue of research for different gravitational stress-based conditions in a broad range of applications like disease management, sports, and astronautics.

► *Please cite this article as:*
Goshvarpour A, Goshvarpour. The Impact of Gravitational Stress on Cardiac Dynamics Using Entropy. Iran J Med Phys 2023; 20: 72-79. 10.22038/IJMP.2022.56462.1944.

## Introduction

Human is frequently under gravitational stress as a natural physical stimulus in active daily life. This stress exerts an influence on cardiovascular function. Changing body position from standing to sitting or lying down and vice versa affects the gradient of hydrostatic pressure from the bottom to top (foot to head), which results in a gravity-wise fluid shift. This change triggers neural responses in the autonomic nervous system (ANS) through sympathetic and parasympathetic arms [1, 2]. Consequently, cardiovascular functions are regulated, such that blood pressure fluctuations due to postural changes are moderated. As a result of the head-up tilt (HUT), a reduction in stroke volume/hypotension occurs as fluids move from the upper organs to the lower ones. Subsequently, through baroreceptors, the sympathetic activity of the heart and vasomotor is augmented, and the parasympathetic nerve activity of the heart is suppressed to increase heart rate and vascular resistance [1-3]. Reverse position change causes increased stroke volume/hypertensive effects, which induces the increased vagal activity of the heart and suppression of sympathetic activity. Accordingly, the heart rate and vascular resistance are diminished [1, 4]. This involvement of the two autonomic nerve arms helps keep stable blood pressure. However, in some diseases, the shift in autonomic arms from the balance to the predominance of one arm is attenuated or absent like in a hypertensive and diabetic person [5, 6]. Several clinical tests are administered to evaluate autonomic function/dysfunction [7]. Heart rate (HR) is a noninvasive one, which has been applied efficaciously to assess autonomic tone modulation. It is sensitive to gravitational stress forced by postural changes [8].

Formerly, some researchers have been fascinated with investigating the effect of postural change and gravitational stress on cardiovascular parameters. In the study performed by Carnethon et al. [8], the mean and standard deviation (SD) of RR intervals were analyzed in the supine and upright positions considering demographic characteristics and

*Corresponding Author: Tel: +98 5138041, Ext. 3131; Email: ak_goshvarpour@imamreza.ac.ir

coronary heart disease (CHD) risk factors. Their results proved the possibility of detecting differences in cardiac autonomic balance by adopting these simple measures. Vuksanovic et al. [9] evaluated the effect of body posture on spectral indices of heart rate variability (HRV) signals in children and young adults with heart disease. Their findings emphasized the difference between HRV spectral measures of healthy and diseased subjects for the change of supine to upright posture. In most participants, the high-frequency (HF) power of HRV was decreased in standing. In brief, the posture response is not distinctive in this age range because of the difference in HF power. Kubo et al. [10] attempted to examine the cardiac changes in six positions, including supine, 30-degree semi-sitting, standing, supine, 90-degree sitting, and standing. They showed a difference in QTc interval on electrocardiograms (ECG) during postural changes, particularly from supine to sitting positions. In another study [11], the P-wave voltage on ECG was evaluated in patients with a history of syncope undergoing HUT. Their findings indicated the impaired P-wave peaking at 75% of HUT-triggered syncope. Ciliberti et al. [12] studied the efficiency of spectral HRV measures in predicting vasovagal syncope during HUT. They showed that the incidence of syncope during HUT could be predicted by the very low frequency (VLF) component at rest. Hnatkova et al. [13] examined the sex-related HRV responses to postural provocations. The subject's position was considered in the following arrangements four times, supine→sitting→standing→supine and supine→standing→sitting→supine. They analyzed the HR and HRV spectral measures. The results showed that regardless of similar increments in heart rate, women respond to standing by more considerable shifts in cardiac sympathovagal modulations. Kumar et al. [14] evaluated some time-domain measures of heart rate variability (HRV) under different postural positions. Precisely, they analyzed some time-domain indices including HR, RR-interval, root mean square of successive differences (RMSSD) between normal heartbeats, standard deviation of normal to normal RR intervals (SDNN), the number of normal to normal RR intervals which differ by more than 50 milliseconds from the previous interval (NN50), proportion of NN50 (pNN50), and some frequency-domain measures like normalized low frequency (LFnu), normalized high frequency (HFnu), the ratio of low frequency to high frequency (LF/HF) during sitting, standing, and lying positions. The results revealed a larger RR interval for lying posture followed by sitting and standing. Moreover, a higher LF/HF ratio was observed, emphasizing a more excessive sympathetic influence.

A review of the literature shows that in all the works, morphological features, time-based characteristics, and spectral measures have been considered, but the dynamics of the heart signal have not been adequately evaluated during gravitational stress. However, the chaotic nature of the bio-data necessitates the use of nonlinear approaches. Entropy is a nonlinear measure that shows the time series uncertainty, irregularity, and complexity [15]. Up to now, several algorithms have been introduced for entropy calculation. The dynamics of the cardiac signal have not been studied adequately for postural changing conditions. Recently, Nardelli et al. [16] studied multichannel physiological complexity during postural changes. They analyzed HRV and blood pressure variability series. They examined the refined generalized multivariate multiscale fuzzy entropy for data analysis. The results indicated the possibility of statistically discriminating the resting and stand-up conditions using entropy. More recently, Rawal and Sethi [17] examined the postural-related changes (lying and standing) in the autonomic activity of healthy young women. They analyzed HRV by the autoregressive model as a frequency-domain approach and sample entropy and approximate entropy as nonlinear methods. Comparative analysis of the effect of the postural change on HRV was performed using paired t-test. Higher entropy measures in the lying posture were shown with no statistically significant difference between the groups for approximate entropy. Although the authors attempted to provide a dynamic analysis, some limitations should be noted. (1) In [16], the authors studied multichannel data, including cardiovascular and diastolic blood pressure variability in a combined form. In this study, we used only one-channel data, which is both easier to record and user-friendly such that it can be implemented in a therapeutic system. (2) In both articles, one/two entropy measures during the supine resting state and active stand-up. In contrast, we studied six-position modes using different entropy indices. (3) In both studies, the authors only looked at the statistical differences between the features in the two resting positions and standing up. In the current study, we analyzed the ability of features to differentiate between groups in a classification problem.

Literature review shows that the characteristics of cardiac signals in different postural conditions have been studied, and no attempt has been made to differentiate and classify them. Precisely, the entropy analysis of HRV was measured from different postural conditions, and its application for automated classification of these states should be proven using a machine learning approach. Previously, some studies have been conducted to investigate entropy measures of various biomedical time-series datasets [18-25]. Pieces of literature indicate the entropy capability in identifying the complexity present in bio-signal using computerized methods. The entropy measures are more resistant to noise than the conventional time/spectral HRV indices.

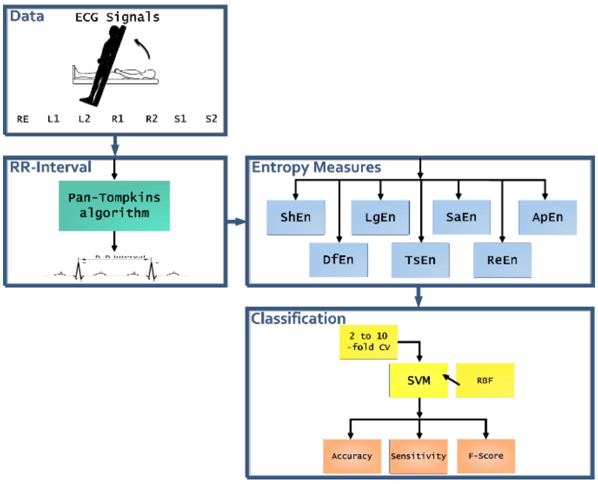



Figure 1. Recommended algorithm. The data includes available ECG signals in six postural positions. The second module estimates the RR intervals of ECGs using the Pan-Tomkins algorithm. Then, different entropy measures are calculated. Finally, the support vector machine (SVM) are applied to identify different postures using a k-fold cross-validation scheme and the accuracy, sensitivity, and F-score of the classifier are reported.

They call for a shorter length of data compared to other nonlinear measures, like the Lyapunov exponents, fractals, and correlation dimensions [26-27]. Thus, in short-term (about 5 minutes) HRV analysis, entropy may provide more reliable fallouts than other nonlinear characteristics [18].

This experiment was intended to develop an automated system for classifying postural changes using ECG signals. To this effect, we estimated the RR intervals of ECGs using the Pan-Tomkins algorithm. Then, some entropies were calculated for each body posture. Finally, we applied the support vector machine (SVM) to identify different postures using a k-fold cross-validation scheme. The planned system is shown in Figure 1.

## Materials and Methods

### *Data*

In this study, the ECG signals were designated from the database available at Physionet [28]. It covers lead II ECG segments of 10 participants. Five women and five men, with a mean age of 28.7±1.2 years, participated in the trial. They were healthy and had a mean weight of 70.6±4.5 kg and a mean height of 172.8±4 cm. Written consent was obtained from subjects before participating in the experiment. The signals were recorded using a standard clinical ECG monitor, FINAPRES, at a sampling rate of 250 Hz.

Subjects were laid on a tilt table with foot support. Their postures changed according to a series of six positions. (1) Over 2 seconds, the bed was tilted to75-degree (Rapid HUTs; R1 & R2). For each subject, it was rehearsed two times. (2) Two stand-ups (S1 & S2), (3) Over 50 seconds, the bed was tilted to75-degree (Low HUTs; L1 & L2). For each subject, it was repeated two times. Each of these phases lasts for three minutes. They were separated by 5 minutes, while the subject was in the resting supine baseline recording (RE). The arrangement of six intercessions was randomized for each participant. The signals were recorded at the MIT General Clinical Research Center [28].

In this study, we used both rapid HUTs, both low HUTs, and both stand-up positions. In addition, we considered the first resting supine recording condition as a baseline. The RR intervals of ECG signals during these postures were estimated using the Pan-Tomkins algorithm for further processing.

### *Entropy indices*

Entropy is a quantifier that indicates the uncertainty/randomness of the data. It is also served as a measure of complexity and the amount of information confined in the time series [29]. To date, many algorithms have been introduced to appraise the entropy of the data. Here, we used several entropy measures to characterize the RR time series, including Shannon entropy (ShEn), Log energy entropy (LgEn), Sample entropy (SaEn), Differential entropy (DfEn), Tsallis entropy (TsEn), Renyi entropy (ReEn), and Approximate entropy (ApEn).

Assume data of size *N*, i.e. $\{X_1, X_2, \ldots, X_N\}$, where its probability mass function is $P(X)$. The ShEn is the simplest form and classic formulation of entropy. It is described as follows:

$$ShEn = -\sum_{i=1}^{N} P(X_i)\log_2 P(X_i) \tag{1}$$

The LgEn is defined by equation (2):

$$LgEn = -\sum_{i=1}^{n} (\log_2 P(X_i))^2 \tag{2}$$

Two values of *m* and *r* should be chosen to estimate SaEn. Subsequently, one should select template vectors (*Xm*) of length *m*. Additionally, *d[Xm(i), Xm(j)]*, which shows the distance function should be selected. Adding the number of vector pairs of length *m* and *m+1* (symbolized by B and A), SaEn is described as follows:

$$\text{SaEn} = -\log \frac{A}{B} \tag{3}$$

In this study, we set *m = 2* and *r = 0.15* of the standard deviation of the data.

The ReEn of order α (where α ≥ 0 and α ≠ 1) is calculated as follows:

$$\mathrm{Re}\,En = -\frac{1}{1-\alpha}\sum_{i=1}^{N} \log P^{\alpha}(X_i) \tag{4}$$

The formulation of the TsEn (where α ≠ 1) is as equation (5):

$$TsEn = -\frac{1}{1-\alpha}\left(1-\sum_{i=1}^{N} P^{\alpha}(X_i)\right) \tag{5}$$

Here, we set α=2 for both ReEn and TsEn.

The DfEn is described as:

$$DfEn = -\int_X P(X)\log P(X)dx \tag{6}$$

For the DfEn, ReEn, and TsEn calculation, we exploited TIM MATLAB 1.2.0. Toolbox [30].

### *Classification*

In this work, the body postures were classified using the support vector machine (SVM). In this procedure, the input attributes were converted into a high-dimensional space. A repetitive learning process, which depends on the input, delivers an optimum hyperplane with the utmost border between the classes. Lastly, these margins will sketch the decision borders over the data groups. The classification performance increases by growing the extent between the hyper-planes and data samples in different categories. To drive the SVM, a kernel function should be taken.

This study applied a radial basis function (RBF) as a kernel function, which is a nonlinear one. In addition, a k-fold cross-validation scheme was implemented, where k varied in the range of 2 to 10; k = 2, 3, 4, 5, 6, 7, 8, 9, and 10. This delivers the profits of avoiding over-fitting and constructing reliable network performances. To categorize the body postures, we adopted two strategies: (1) one group vs. all other remaining groups (OVA) and (2) one body posture vs. the resting supine position (BVR). Accuracy (AC), Sensitivity (Se), and F1-Score (F1) were intended to assess the network performance.

## Results

As described in previous sections, different entropy measures namely ShEn, LgEn, SaEn, DfEn, TsEn, ReEn, and ApEn of the RR intervals were calculated. Figure 2 shows the mean and standard deviation (std) of the entropies in different positions.

As the figure shows, for different postural body positions, the mean ShEn values vary between 61.45 (R1) and 90.85 (L1). The lowest mean LgEn is -203.5 for S1, and its highest value is -103.21 for RE. The highest/lowest mean SaEn is 1.65/1.35 for RE/L1. Inversely, the RE/L1 has the lowest/highest mean DfEn (-2.26/-1.62). The lowest mean TsEn is -12.53 for L1, and its highest value is -5.9 for S1. The highest/lowest mean ReEn is -1.86/-2.39 for L2/RE. The lowest mean ApEn is 0.96 for S1, and its highest value is 1.19 for RE.

A significant difference between different body postures and resting supine position was inspected by ANOVA and Tukey procedure (also known as Tukey's Honest Significant Difference (HSD) test). Table 1 shows the statistical results, including the p- and F-values and the HSD test.

Considering all positions, the most significant differences between the groups were found for the ApEn. In contrast, the results showed there were no significant differences between the ShEn of postural conditions and resting state. By examining the significance of the entropy values in different positions, it can be uncovered that the most significant differences were observed between the resting state and two slow HUTs (L1 & L2).

As mentioned before, two strategies have been adopted to classify the body postures: OVA and BVR. The former evaluates the scheme's performance in separating each class from all other groups. The latter assesses the system’s performance in differentiating each category from a resting supine position. Figure 3 shows the OVA classification performances, and the BVR performances have been presented in Figure 4.

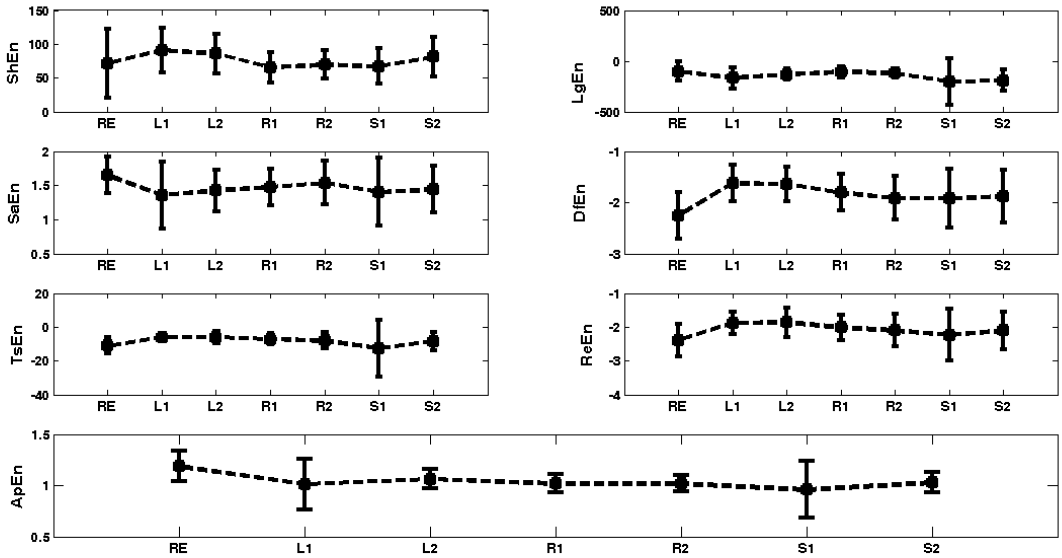
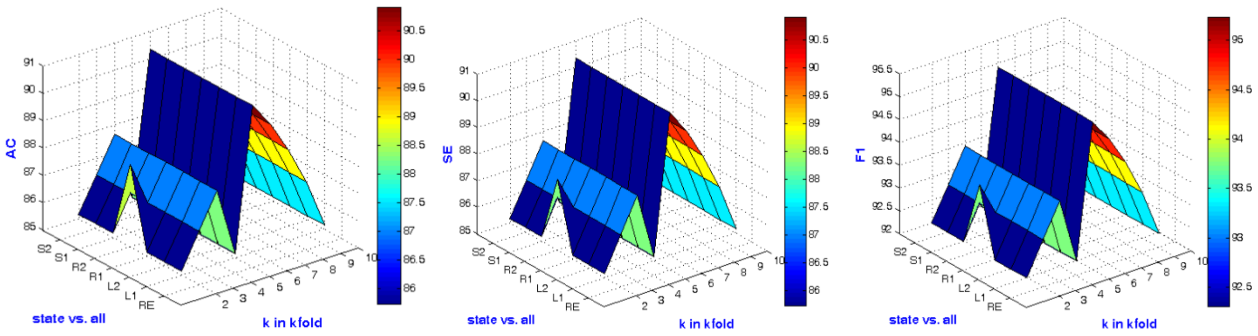



Figure 2. Variations of different entropy measures in dissimilar postural conditions. Note- RE: rest, L1 & L2: two low HUTs; R1 & R2: two rapid HUTs; S1 & S2: two stand-ups.

Table 1. Statistical differences between entropy measures of different postural states and resting positions using RR intervals.

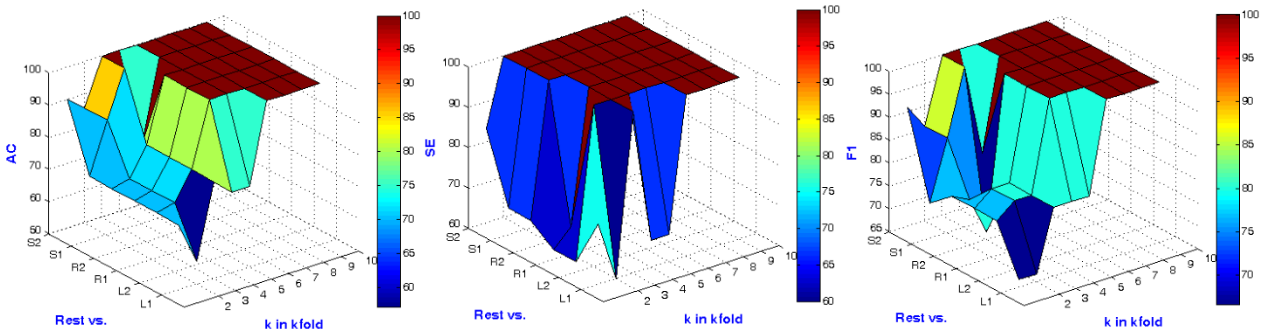
| | | *p*-value | *F*-value | | *p*-value | *F*-value |
|---|---|---|---|---|---|---|
| | ShEn | 0.31 | 1.05 | | 0.44 | 0.6 |
| | LgEn | 0.16 | 2.04 | | 0.38 | 0.8 |
| | SaEn | 0.11 | 2.67 | | 0.1 | 2.96 |
| RE vs. L1 | DfEn | 0.002* | 12.23 | RE vs. L2 | 0.002* | 11.87 |
| | TsEn | 0.01* | 8.24 | | 0.018* | 6.67 |
| | ReEn | 0.01* | 7.93 | | 0.017* | 6.84 |
| | ApEn | 0.07 | 3.63 | | 0.04* | 4.79 |
| | ShEn | 0.74 | 0.11 | | 0.91 | 0.01 |
| | LgEn | 0.87 | 0.02 | | 0.66 | 0.2 |
| | SaEn | 0.17 | 2.006 | | 0.42 | 0.6 |
| RE vs. R1 | DfEn | 0.02* | 6.02 | RE vs. R2 | 0.1 | 3.005 |
| | TsEn | 0.051 | 4.34 | | 0.2 | 1.74 |
| | ReEn | 0.06 | 3.93 | | 0.17 | 1.96 |
| | ApEn | 0.007* | 9.25 | | 0.005* | 9.97 |
| | ShEn | 0.82 | 0.04 | | 0.6 | 0.28 |
| | LgEn | 0.21 | 1.63 | | 0.06 | 3.99 |
| | SaEn | 0.18 | 1.87 | | 0.15 | 2.22 |
| RE vs. S1 | DfEn | 0.16 | 2.13 | RE vs. S2 | 0.1 | 2.97 |
| | TsEn | 0.78 | 0.07 | | 0.29 | 1.17 |
| | ReEn | 0.59 | 0.29 | | 0.24 | 1.46 |
| | ApEn | 0.03* | 5.3 | | 0.01* | 7.92 |

*: HSD results*




(a) (b) (c)

Figure 3. OVA classification performances. (a) Accuracy (AC), (b) Sensitivity (SE), and (c) F1-score (F1).
Note – RE: rest, L1 & L2: two low HUTs; R1 & R2: two rapid HUTs; S1 & S2: two stand-ups. We used a k-fold cross-validation strategy for partitioning data into training and test; where k was set into 2 to 10.




(a) (b) (c)

Figure 4. BVR classification performances. (a) Accuracy (AC), (b) Sensitivity (SE), and (c) F1-score (F1).
Note – RE: rest, L1 & L2: two low HUTs; R1 & R2: two rapid HUTs; S1 & S2: two stand-ups. We used a k-fold cross-validation strategy for partitioning data into training and test; where k was set into 2 to 10.

The figure indicates that the highest OVA classification accuracy rate is about 90.91% for 6-fold cross-validation, while it varies in the range of about 85.7 to 90.9% for all k values. The sensitivity range is identical to the accuracy, and F1 values fluctuate between 92.31 and 95.24%.

The figure indicates that the highest BVR classification accuracy rate is 100% for discrimination of all states using 7-fold, 8-fold, 9-fold, and 10-fold cross-validation, while it varies in the range of about 57.14 to 100% for all k values. The sensitivity range is 60 to 100%, and F1 values fluctuate between 66.67 and 100%. The most inferior classification performances are indicated for 3-fold cross-validation.

## Discussion

In the present work, we evaluated the uncertainty of RR intervals during different postural positions using entropy measures. In addition, an automated system was developed to classify different bodily positions. In this regard, two strategies were adopted, namely OVA and BVR. The SVM was used to categorize the postures using a k-fold cross-validation scheme with different k values. Experimental results established fascinating achievements. (1) Using statistical analysis, ApEn revealed the most significant differences between the groups, while there were no significant differences between the ShEn of postural conditions and resting state. In addition, the most significant differences were perceived between the resting state and two slow HUTs (L1 & L2). (2) BVR outperformed the OVA in terms of higher classification performances, where the classification accuracy was 100%. (3) For each k of k-fold, the OVA classification performance values were almost independent of the position understudy, although this was not the case in BVR.

A summary of distinctive techniques used for evaluating the impact of postural body positions on the cardiac system is presented in Table 2.

In [8], the authors evaluated the relation between the shift in HRV with postural change and the demographic characteristics as well as coronary heart disease (CHD) risk factors. Studying a large population sample revealed the shift in autonomic balance from active postural change using short-term HRV. The results indicated that obesity, hypertension, and diabetes cause smaller changes in R-R intervals and larger changes in SD of R-R intervals with a standing position. In contrast, no differences were found in the spectral measures by CHD risk factors. In [28], the short-term transient hemodynamic response to the upright posture for rapid tilt, slow tilt, and standing up was inspected using HR and arterial blood pressure. The signals steady-state responses were independent of the transition mode to the head-up position. Kubo et al. [10] showed an extended QTc interval in the supine position compared to that in the sitting and the standing position. The results of the Vuksanovich study [9] were not converged for changing position using frequency analysis of cardiac signal when. They reported two types of responses; in the majority of the subjects, a decrease, and in about one-third of subjects increase in HF power was observed.

Table 2. Summary of different frameworks to assess the impact of postures on the cardiac system.

| Literature | Subject | Positions | Methodology | Results |
|---|---|---|---|---|
| [8] | 7686 men and women | Supine/ standing | mean and standard deviation of R-R intervals considering demographic characteristics and coronary heart disease risk factors | the possibility of detecting differences in cardiac autonomic balance using these simple measures |
| [28] | 5 males and 5 females | Rest/ rapid tilts/ slow tilts/ stand up | HR & arterial blood pressure | A marked initial transient drop in mean arterial pressure and an increase in HR were seen during rapid tilt and stand-up |
| [10] | 72 males | Supine/30° semi-sitting/standing/ supine/90° sitting/ standing | QT/QTc intervals | A difference in QTc interval on ECG during supine to sitting position |
| [9] | 41 cardiac patients | Supine/ standing | spectral indices of HRV in children and young adults with heart disease | A decrease in the high-frequency power of HRV in standing |
| [13] | 175 females and 176 males | Supine/sitting/standing | Spectral indices of HRV | Women reacted to standing by more substantial shifts in cardiac sympathovagal modulations. |
| [14] | 5 males and 5 females | Sitting/standing/lying | time-domain and frequency-domain measures of HRV | A larger RR interval and a higher LF/HF ratio for lying |
| [16] | 5 males and 5 females | Supine/ standing | Multiscale Fuzzy Entropy | it is possible to statistically discriminate the positions |
| [17] | 20 females | Supine/ standing | the autoregressive model and SaEn and ApEn | Higher entropy measures in the lying posture, but no statistically significant difference between the groups for ApEn |
| Present work | 5 males and 5 females | Rest/ 2 rapid tilts/ 2 slow tilts/ 2 stand up | Different entropy measures, SVM classification in two modes: OVA and BVR. The | The most significant differences between the groups using ApEn The highest classification rate of 100% for BVR |

Hnatkova et al. [13] evaluated sex differences in HR and HRV responses to two postural provocative tests. Regardless of gender, switching from a supine position to standing leads to a sharp increase in HR elevation. However, HRV analysis established considerable differences in the HF and LF HR modulations in females and males. These results are in line with Rawal and Sethi's study [17], where it was concluded that the HR is considerably higher and HRV is lower in standing as compared to the supine position. Evaluating different time-domain and frequency-domain indices of HR in sitting, standing, and sleeping conditions revealed a larger RR interval for sleeping followed by sitting and standing and a higher LF/HF ratio for sleeping [14]. The possibility of statistically discriminating the supine and standing positions using multiscale fuzzy entropy was also confirmed in [16]. The results of the present study are somewhat in line with the results of these studies, all of which indicate that some cardiac parameters are affected by gravitational stress. However, the results of our study also showed the separability of the parameters in a classification problem.

\In brief, the experimental findings of this study indicate that our approach is comparable with the previously reported frameworks. In addition, we evaluated a classification approach to recognize the positions accurately. The proposed algorithm served to provide a reliable human postural classification system utilizing nonlinear dynamics of the cardiac system. This effort provides an applicable scheme, which would be suitable for several practical demands. Not only in some heart diseases such as diabetes and hypertension but also in some conditions like mountaineering, rock climbing, parachuting, high altitude, and astronautics, the effect of gravitational stress on physiological parameters, especially the heart, becomes a crucial issue.

Notwithstanding the benefits mentioned, there are some deficiencies that to be considered. Here, the maximum accuracy was 100% employing a simple classifier, SVM. However, the number of participants for system evaluation was limited. A considerable number of signals in different postural positions should be examined to validate the framework. We managed the available database [28], where the ECG signals of healthy participants were provided. Since gravitational stress can be realized in different pathological as well as environmental conditions, the performance of the scheme should be carefully evaluated in the future. Another limitation is the dependence of HR changes in different positions on demographic factors [8, 13]. It is suggested that in future works, considering these factors, the results be examined more carefully. The available data are derived from the study of healthy individuals. Therefore, we cannot comment on whether there are similar dynamic changes in patients with cardiac and/or autonomic disorders such as diabetes. This should be explored in future work.

## Conclusion

In this study, we tested two novel aspects in evaluating the effect of gravitational stress on cardiac parameters. First, we examined the entropy property as a nonlinear measure of the signals, while in previous studies, the signal dynamics under these conditions had not been investigated adequately. Second, we addressed the issue of a classification approach. To this effect, different entropy measures, namely ShEn, LgEn, SaEn, DfEn, TsEn, ReEn, and ApEn of the R-R intervals, were calculated while participants were in supine rest, in two rapid HUTs, two stand-ups, and two slow HUTs. Then, the OVA and BVR classification strategies were adopted using SVM. The proposed approach delivered an outstanding performance with high classification rates over the different postural changes. The best performance rates were 100% for the BVR scheme. The present methodology can be extended for several gravitational stress-based conditions in a massive range of applications like disease management, sports, and astronautics.

## Acknowledgment

The authors would like to thank Dr. Thomas Heldt and his colleagues for the open sharing of the database.

## References

1. Miwa C, Sugiyama Y, Mano T, Matsukawa T, Iwase S, Watanabe T, et al. Effects of aging on cardiovascular responses to gravity-related fluid shift in humans. The Journals of Gerontology Series A: Biological Sciences and Medical Sciences. 2000 Jun 1;55(6):M329-35.
2. Mukai S, Hayano J. Heart rate and blood pressure variabilities during graded head-up tilt. Journal of Applied Physiology. 1995 Jan 1;78(1):212-6.
3. Iwase S, Mano T, Watanabe T, Saito M, Kobayashi F. Age-related changes of sympathetic outflow to muscles in humans. Journal of gerontology. 1991 Jan 1;46(1):M1-5.
4. Miwa C, Mano T, Saito M, Iwase S, Matsukawa T, Sugiyama Y, et al. Ageing reduces sympatho-suppressive response to head-out water immersion in humans. Acta physiologica scandinavica. 1996 Aug;158(1):15-20.
5. Guzzetti S, Piccaluga E, Casati R, Cerutti S, Lombardi F, Pagani M, et al. Sympathetic predominance in essential hypertension: a study employing spectral analysis of heart rate variability. Journal of hypertension. 1988 Sep 1;6(9):711-7.
6. Pagani M, Malfatto G, Pierini S, Casati R, Masu AM, Poli M, et al. Spectral analysis of heart rate variability in the assessment of autonomic diabetic neuropathy. Journal of the autonomic nervous system. 1988 Aug 1;23(2):143-53.
7. Pfeifer M. Cardiovascular assessment. In: Dyck PJ, Thomas P, editors. Diabetic neuropathy. 2nd ed. Philadelphia: WB Saunders; 1999; 171-84.
8. Carnethon MR, Liao D, Evans GW, Cascio WE, Chambless LE, Heiss G. Correlates of the shift in heart rate variability with an active postural change in a healthy population sample: The Atherosclerosis

Risk In Communities study. American heart journal. 2002 May 1;143(5):808-13.
9. Vuksanovic V, Gal V, Kalanj J, Simeunovic S. Effect of posture on heart rate variability spectral measures in children and young adults with heart disease. International journal of cardiology. 2005 May 25;101(2):273-8.
10. Obata Y, Ruzankin P, Ong QJ, Berkowitz DE, Berger RD, Steppan J, Barodka V. The impact of posture on the cardiac depolarization and repolarization phases of the QT interval in healthy subjects. Journal of Electrocardiology. 2017 Sep 1;50(5):640-5.
11. De Gregorio C, Lentini C, Grimaldi P, Zagari D, Andò G, Di Bella G, et al. P-wave voltage and peaking on electrocardiogram in patients undergoing head-up tilt testing for history of syncope. European Journal of Internal Medicine. 2014 Apr 1;25(4):383-7.
12. Ciliberti MA, Santoro F, Di Martino LF, Rinaldi AC, Salvemini G, Cipriani F, et al. Predictive value of very low frequency at spectral analysis among patients with unexplained syncope assessed by head-up tilt testing. Archives of Cardiovascular Diseases. 2018 Feb 1;111(2):95-100.
13. Hnatkova K, Šišáková M, Smetana P, Toman O, Huster KM, Novotný T, et al. Sex differences in heart rate responses to postural provocations. International journal of cardiology. 2019 Dec 15;297:126-34.
14. Kumar P, Das AK, Halder S. Time-domain HRV analysis of ECG signal under different body postures. Procedia Computer Science. 2020 Jan 1;167:1705-10.
15. Pincus SM, Gladstone IM, Ehrenkranz RA. A regularity statistic for medical data analysis. Journal of Clinical Monitoring. 1991 Oct;7(4):335-45.
16. Nardelli M, Scilingo EP, Valenza G. Refined generalized multivariate multiscale fuzzy entropy: A preliminary study on multichannel physiological complexity during postural changes. In2018 26th European Signal Processing Conference (EUSIPCO). 2018; 291-5.
17. Rawal K, Sethi G. HRV analysis of different postures of young healthy women using signal processing methods. Biomedical Engineering: Applications, Basis and Communications. 2021 Feb 30;33(01):2150006.
18. Byun S, Kim AY, Jang EH, Kim S, Choi KW, Yu HY, et al. Entropy analysis of heart rate variability and its application to recognize major depressive disorder: A pilot study. Technology and Health Care. 2019 Jan 1;27(S1):407-24.
19. Kang J, Chen H, Li X, Li X. EEG entropy analysis in autistic children. Journal of Clinical Neuroscience. 2019 Apr 1;62:199-206.
20. Wang F, Wang H, Fu R. Real-time ECG-based detection of fatigue driving using sample entropy. Entropy. 2018 Mar 15;20(3):196.
21. Horie T, Burioka N, Amisaki T, Shimizu E. Sample entropy in electrocardiogram during atrial fibrillation. Yonago Acta Medica. 2018;61(1):049-57.
22. Xue SW, Yu Q, Guo Y, Song D, Wang Z. Resting-state brain entropy in schizophrenia. Comprehensive Psychiatry. 2019 Feb 1;89:16-21.
23. Acharya UR, Hagiwara Y, Koh JE, Oh SL, Tan JH, Adam M, et al. Entropies for automated detection of coronary artery disease using ECG signals: A review. Biocybernetics and Biomedical Engineering. 2018 Jan 1;38(2):373-84.
24. Molina V, Bachiller A, Gomez-Pilar J, Lubeiro A, Hornero R, Cea-Cañas B, et al. Deficit of entropy modulation of the EEG in schizophrenia associated to cognitive performance and symptoms. A replication study. Schizophrenia Research. 2018 May 1;195:334-42.
25. Thul A, Lechinger J, Donis J, Michitsch G, Pichler G, Kochs EF, et al. EEG entropy measures indicate decrease of cortical information processing in Disorders of Consciousness. Clinical Neurophysiology. 2016 Feb 1;127(2):1419-27.
26. Eckmann JP, Ruelle D. Fundamental limitations for estimating dimensions and Lyapunov exponents in dynamical systems. Physica D: Nonlinear Phenomena. 1992 May 1;56(2-3):185-7.
27. Bolea J, Laguna P, Remartínez JM, Rovira E, Navarro A, Bailón R. Methodological framework for estimating the correlation dimension in HRV signals. Computational and mathematical methods in medicine. 2014 Jan 1;2014.
28. Heldt T, Oefinger MB, Hoshiyama M, Mark RG. Circulatory response to passive and active changes in posture. InComputers in Cardiology. 2003; 263-6.
29. Pincus SM. Approximate entropy as a measure of system complexity. Proceedings of the National Academy of Sciences. 1991 Mar 15;88(6):2297-301.
30. Rutanen K. Tim matlab 1.2.0. Matlab toolbox. 2011; Available at: https://www.cs.tut.fi/~timhome/tim/tim/matlab/directory.htm