Markov Transition Matrix Analysis Reveals Age-Dependent Patterns in Symbolic Heart Rate

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Abstract

To understand how the heart responds to physiological demands, heart rate variability (HRV) has been explored extensively in previous literature. However, less attention has been given to how beat-to-beat directional changes in HR, deceleration, acceleration, or no change, evolve across the lifespan. In this study, we applied a Markov transition matrix approach to electrocardiogram (ECG) data from 56 healthy participants to examine age-related differences in symbolic HR transitions. The participants were divided into two age groups: young (18–19 years old, n = 40) and advanced age (75–92 years old, n= 16). The transition matrix was constructed based on three states: HR deceleration (state -1), no change in HR (state 0), and HR acceleration (state 1). The results of this analysis show significant differences between the young and advanced age groups in terms of transitioning from state -1 to the other states. Additionally, the probability of transitioning to state 0 from another state is higher in the advanced age group compared to the young group. Both findings suggest a reduction in parasympathetic activity and HRV.

1. Introduction

Heart rate variability (HRV) has been used as a general indicator of autonomic nervous system (ANS) activity. HRV refers to the beat-to-beat variations in heart rate, also known as RR intervals (RRIs), and is believed to be modulated by both the parasympathetic and sympathetic branches of the ANS [1, 2]. HRV serves as a rough marker of cardiac health and fitness and has been extensively used for ANS related inferences [3–5]. Previous studies have demonstrated that both the time and frequency domains of HRV decline with age, suggesting a reduction in parasympathetic activity and an increase in sympathetic activity [2, 5]. Specifically, the standard deviation of normal-to-normal RR intervals (SDNN) and the high-frequency (HF) band of HRV, both indicators of parasympathetic activity, have been shown to decrease with age [5].

Conventional HRV measures typically ignore the directionality of RR interval (RRI) fluctuations, that is, whether the heart rate (HR) is decelerating or accelerating. The analysis of this directional behavior is known as heart rate asymmetry (HRA), originally characterized using Poincaré plots [6]. HRA quantifies the relative contribution of HR accelerations and decelerations to overall HRV [7, 8], and has also been examined through the study of monotonic runs of accelerations and decelerations [8, 9]. Beyond traditional HRV and HRA, symbolic HRV [10, 11] provides an additional framework for capturing directionality by transforming RRIs into discrete symbolic sequences, allowing for the analysis of temporal patterns and state transitions. Together, HRA and symbolic HRV can offer deeper insights into how the sinoatrial node responds differently to accelerations versus decelerations, responses that are influenced by multiple physiological factors, including autonomic nervous system activity, electrolyte balance, and hormonal regulation [6].

So far, the mechanisms associated with HRV directionality are not well understood, and further research is needed to explore the prognostic value of studying HRV directionality and its changes with physiological aging. Here, we employ the Markov transition matrix [12] to investigate the transition patterns between accelerations and decelerations in healthy participants. From the transition matrix, transition probabilities were calculated to examine how these patterns change with age.

2. Methods

2.1. Data description

In this study, electrocardiogram (ECG) signals from the online publicly available "Autonomic Aging: A dataset to quantify changes of cardiovascular autonomic function during healthy aging" Physionet database were used [13–15]. Information related to participants' recruitment and data collection is explained in detail in [15]. Simultaneous records of ECG and continuous blood pressure were collected from 1,121 healthy subjects with a sampling rate

of 1000 Hz, age: 18-92 years old. Informed written consent was collected from all subjects, and all research was performed in accordance with relevant guidelines and regulations. The length of the recordings ranged from 8 to 35 minutes.

In PhysioNet, the exact age associated with each record is not reported; instead, participant data are grouped into 15 age-based categories. In this study, we considered Group 1 (18 – 19 years), Group 13 (75 – 79 years), Group 14 (80 – 84 years), and Group 15 (85 – 92 years). The reason for selecting multiple groups from the advanced aging category was to balance the number of samples between the young and aged groups. The number of available ECG records per group was as follows: Group 1: $n = 46$, Group 13: $n = 7$, Group 14: $n = 12$, and Group 15: $n = 7$.

2.2. ECG R peak detection

Here, we considered 5-minutes of ECG records per participant. Only ECG signals with clear R peaks were considered. ECG records with noise or hard-to-detect R peaks were not considered. Further, ECG signals with a lot of ectopic beats were excluded. After exclusion, the number of samples per group was: Group 1: $n = 40$ (male: 8, female: 39, unknown gender: 1), Group 13: $n = 5$ (all female), Group 14: $n = 5$ (all female), and Group 15: $n = 6$ (all female). R peaks were detected in MATLAB 2023b by using a code based on the "findpeaks" function.

2.3. Markov Transition matrix and probability calculation

To construct the Markov transition matrix, we identified three states based on consecutive RRI beats as follows (the subscript x indicates the beat count):

- State -1: HR deceleration ($RR_{x+1} - RR_x > 0$).
- State 0: no change in RRI ($RR_{x+1} - RR_x = 0$).
- State 1: HR acceleration ($RR_{x+1} - RR_x < 0$).

A 3 x 3 transition matrix, which contains the transition probability (TP), was constructed. In the transition matrix, TP $(i \rightarrow j)$ denotes the probability of transitioning from state *i* to state *j*. Table 1 shows an illustration of the transition matrix that was used in this study per participant. In the table, TP $(-1 \rightarrow -1)$ indicates a monotonic deceleration run or the probability of transitioning from state -1 (HR deceleration) to state -1 (HR deceleration). The sum of the probabilities in each row is 1.

2.4. Statistical analysis

We created two age-based groups: Group 1 (young, 18 – 19 years old, $n = 40$) and Group 2 (advanced age, 75 – 92 years old, $n = 16$). We compared the mean values using the Wilcoxon rank-sum test in MATLAB.

3. Results

3.1. Transition from state -1 (HR deceleration)

A comparison between the transition matrix of young and advanced age groups revealed that all transitions from state -1 were significant, TP (-1 $\rightarrow$ -1) ($p < 0.05$), TP (0 $\rightarrow$ -1) ($p < 0.05$), and TP (-1 $\rightarrow$ 1) ($p < 0.05$). In transition from -1, the tendency to continue on declaration runs are higher in the young group (TP = 0.051 ± 0.09) compared to the advanced age group (TP = 0.42 ± 0.11). Opposite trends are observed in transitioning from -1 to either 0 or 1 where the TP values were higher in the advanced age group (TP (-1 $\rightarrow$ 0) = 0.03 ± 0.03, TP (-1 $\rightarrow$ 1) = 0.54 ± 0.12) compared to the young group (TP (-1 $\rightarrow$ 0) = 0.012 ± 0.01, TP (-1 $\rightarrow$ 1) = 0.48 ± 0.09) .

3.2. Transition from state 0 (no change)

There are no significant differences when transitioning from state 0 to state -1 or 1. However, the TP (0 $\rightarrow$ 0) is slightly higher in the advanced age group. The table further reveals that there is less tendency to transition to state 0 from any other state where all probabilities were almost zero in both groups.

3.3. Transition from state 1 (HR acceleration)

There are no significant differences when transitioning from state 1 to state -1, or 1. However, the TP (0 $\rightarrow$ 0) is significantly higher in the advanced age group ($p < 0.05$).

4. Discussion

In this study, we explored the transition patterns in HR decelerations and accelerations using a Markov Transition matrix. Our main finding is that the tendency to transition from an HR deceleration state to any other state changes with aging (Table 2). The findings in Table 2 suggest that monotonic deceleration runs (TP (-1 $\rightarrow$ -1)) are more common in the young group compared to the advanced age group. A likely interpretation of this phenomenon is reduced parasympathetic nervous system activity and increased sympathetic nervous system activity in the aging group, as discussed in previous literature [5, 16]. The increase in the sympathetic nervous system activity is further supported by the greater tendency to switch from HR deceleration to HR acceleration in the advanced aging group compared to the young group. Nevertheless, we cannot attribute the observed changes in transition trends exclusively to ANS activity, as other factors, such as respiration

Table 1. Demonstration of the Transition Matrix for Heart Rate Acceleration and Deceleration

State	-1	0	1
-1	TP (-1 → -1) Monotonic HR deceleration run	TP (-1 → 0) No change in HR value from a deceleration state	TP (-1 → 1) Transition to HR acceleration from deceleration
0	TP (0 → -1) Transition from no change to HR deceleration	TP (0 → 0) No change in HR value	TP (0 → 1) Transition from no change to HR acceleration
1	TP (1 → -1) Transition to HR deceleration from acceleration	TP (1 → 0) No change in HR value from an acceleration state	TP (1 → 1) Monotonic HR acceleration run

-1: heart rate (HR) declaration, 0: no change, 1: HR acceleration

Table 2. Comparison between the young and advanced age groups in terms of the transition probabilities

Transition Probability	Young age	Advanced Age	p - value
Transition from state -1 (HR deceleration)			
TP (-1 → -1)	0.51 ± 0.09	0.42 ± 0.11	0.009
TP (-1 → 0)	0.012 ± 0.01	0.03 ± 0.03	0.001
TP (-1 → 1)	0.48 ± 0.09	0.54 ± 0.12	0.047
Transition from state 0 (no change)			
TP (0 → -1)	0.49 ± 0.34	0.46 ± 0.24	0.56
TP (0 → 0)	0.01 ± 0.08	0.02 ± 0.035	0.01
TP (0 → 1)	0.49 ± 0.34	0.46 ± 0.24	0.56
Transition from state 1 (HR acceleration)			
TP (1 → -1)	0.47 ± 0.11	0.52 ± 0.11	0.47
TP (1 → 0)	0.01 ± 0.01	0.034 ± 0.025	p <0.001
TP (1 → 1)	0.51 ± 0.10	0.45 ± 0.11	0.11

The values in the table indicate mean ± Standard deviation

(inspiration and expiration) and hormonal influences, are also believed to play a role in HRV [8].

Another notable finding is that the tendency to switch to the no change state, although very low ($0.01 < \text{TP} < 0.35$), is higher in the advanced age group. This could be attributed to the decline in HRV [2, 16]. Our findings related to transitions from state 1 to state -1 or 1 were not significant ($p < 0.05$). This may indicate that the mechanisms controlling HR accelerations are not affected by age, but more research is needed to understand this.

For further validation of the results, the study should be repeated with a larger sample size. Here, we were limited by the small sample size in the advanced age group. Furthermore, the study would be more comprehensive if we could compare the transition matrix between genders; however, our sample consisted mainly of females. In addition, correlation analysis between HRV and TP could provide deeper insights, but due to space limitations, we could not include such analysis in this manuscript.

Finally, it is worth noting that symbolic HRV analysis, as used in this study, offers a framework that can be integrated with automated techniques, such as machine learning and advanced pattern recognition, to enhance the detection and classification of disease states from ECG recordings as was discussed previously [17].

5. Conclusion

This study demonstrates that age influences the transition dynamics of HR decelerations and accelerations, as quantified by a Markov transition matrix. Younger individuals exhibited more frequent monotonic deceleration runs, suggesting shifts in autonomic balance with aging. Although these patterns are likely linked to reduced parasympathetic and increased sympathetic activity, other physiological factors may also contribute.

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