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Differences of Hjorth Parameters Between Healthy Population and Patients with Valvular Heart Disease in Electrocardiograms, Seismocardiograms, and Gyrocardiograms

https://doi.org/10.1515/cdbme-2025-0170

Abstract: Valvular heart disease (VHD) is the third most common cause of death in the world and constitutes a significant concern for global health. Traditional diagnostic methods, such as echocardiography, computed tomography, and magnetic resonance imaging, are effective, but their limitations in outpatient monitoring have led to exploration of alternative techniques based on wearable inertial measurement unit (IMU) sensors. This study examined differences in Hjorth parameters (activity, mobility, and complexity) between 29 healthy individuals and 30 patients with VHD using electrocardiograms (ECG signals), seismocardiograms (SCG signals), and gyrocardiograms (GCG signals) in healthy subjects from two public datasets: “Mechanocardiograms with ECG reference” dataset and “An Open-access Database for the Evaluation of Cardio-mechanical Signals from Patients with Valved Heart Diseases”, respectively. No significant differences in complexity for all signals and activity in SCG signals were observed. Statistically significant differences (two-sample t-test, $p<0.05$) in mobility for ECG signals and in activity for GCG signal highlight their potential in distinguishing VHD patients from healthy individuals. The study supports the potential of signal-based markers for wearable cardiac monitoring. Future research should focus on larger and more diverse datasets, machine learning-based classification, and clinical integration to improve cardiac diagnostics.

Keywords: Hjorth Parameters; Valvular Heart Disease; Electrocardiography; Seismocardiography, Gyrocardiography

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1 Introduction

Cardiovascular diseases remain the most common cause of death in the world and constitute a significant concern for global health despite recent advances in prevention, diagnosis, and therapy [1, 2]. In recent years, we observed the growing prevalence of valvular heart disease (VHD) in low- and middle-income countries due to the aging population, cardiovascular risk, and socioeconomic disparities that affect the survival rate and healthcare costs [3–6].

Valvular heart disease is defined as a cardiovascular disease that affects any heart valve (aortic valve, mitral valve, pulmonic valve, and tricuspid valve) [7, 8]. The main causes of VHDs are rheumatic heart disease and aging [3, 4, 8, 9]. The most prevalent VHD is aortic stenosis (AS), which is the third most common cardiovascular disease after hypertension and coronary artery disease, and is usually caused by degenerative calcification of the aortic valve or progressive stenosis of a congenital bicuspid valve [8].

Although traditional diagnostic methods, such as echocardiography, computed tomography, and magnetic resonance imaging are effective, their limitations in outpatient monitoring have led to exploration of alternative techniques [3], such as exercise electrocardiography (ECG) [10], seismocardiography (SCG) and gyrocardiography (GCG), which assess cardiovascular function with wearable inertial measurement unit (IMU) sensors placed on a chest [11–13].

Hjorth parameters are statistical functions that represent signal properties in both time and frequency domains that were introduced by Bo Hjorth in 1970 for electroencephalography and usually consist of activity, mobility, and complexity [14, 15], however, they have been applied for other signals, such as ECG [15], SCG, and GCG [16]. Because Hjorth parameters are based the signal variance, they have a lower computational cost than other methods [17, 18].

In this study we evaluated statistically the differences between Hjorth parameters (activity, mobility, complexity) in ECG, SCG, and GCG signals in healthy population and patients with VHD that could be helpful in differentiating the aforementioned populations.

2 Material and Methods

2.1 Datasets

The study was carried out on 59 concurrent recordings of ECG, SCG, and GCG signals taken from two public datasets: 29 were taken from "Mechanocardiograms with ECG reference" published by Kaisti et al. [19, 20] containing signals acquired from twenty-nine healthy volunteers and thirty signals derived from "An Open-access Database for the Evaluation of Cardio-mechanical Signals from Patients with Valvular Heart Diseases" published by Yang et al. in [13, 21].

Recordings from the first dataset were acquired from 29 healthy male volunteers that were registered with sensors described in [19], which were attached to the chest wall over the sternum with a double-sided tape at a sampling frequency of 800 Hz [19, 20, 22]. The second dataset consists of 30 concurrent recordings of raw ECG, SCG and GCG signals with annotated heartbeats taken from 30 patients admitted to Columbia University Medical Center (New York City, NY, USA) before any treatment [13]. All of them had aortic stenosis, 9 patients had tricupsid valve regurgitation (TR), 5 had mitral valve stenosis (MS), 4 with mitral valve regurgitation (MR), and no patients with aortic valve regurgitation.

The ECG, SCG and GCG signals were recorded with Shimmer 3 ECG module (Shimmer Sensing, Dublin, Ireland) with a sampling frequency of 256 Hz (recordings UP-01 to UP-21) and 512 Hz (recordings UP-22 to UP-30). Before measurements, each subject gave their informed consent by signing a consent form. All metadata were deidentified before publication [13, 21].

2.2 Signal processing and statistical analysis

For all signals, we calculated the Hjorth parameters (activity, mobility and complexity [14]), which approximate signal activity and mean power, mean frequency, and signal bandwidth, respectively, and are defined as follows [14, 18, 23]:

$$Activity = {\sigma_x}^2 \tag{1}$$

$$Mobility = \sqrt{\frac{{\sigma_d}^2}{{\sigma_x}^2}} = \frac{\sigma_d}{\sigma_x} \tag{2}$$

$$Complexity = \sqrt{\frac{\frac{\sigma_{dd}^2}{\sigma_d^2}}{\frac{{\sigma_d}^2}{{\sigma_x}^2}}} = \frac{\frac{{\sigma_{dd}}^2}{\sigma_d}}{\frac{\sigma_d}{\sigma_x}} \tag{3}$$

where ${\sigma_x}^2$ is the signal variance, σ_x is the standard deviation of x, σ_d is the standard deviation of the first derivative of x, and σ_{dd} represents the standard deviation of the second derivative of x.

Statistical significance of differences between activity, mobility, and complexity of ECG, SCG, and GCG signals from both analyzed datasets were evaluated with the two-sample t-test with $p < 0.05$ and a default significance level $\alpha = 0.05$. Data preprocessing and statistical analysis was carried out in MATLAB R2024b Update 5 running on Apple MacBookPro 16 inch from October 2024 with macOS 15.3.1.

3 Results

Table 1 and Table 2 present descriptive statistics (mean, standard deviation (SD), minimum (Min), median, maximum (Max)) of Hjorth parameters derived from ECG, SCG, and GCG signals in healthy subjects from "Mechanocardiograms with ECG reference" dataset and "An Open-access Database for the Evaluation of Cardio-mechanical Signals from Patients with Valvular Heart Diseases", respectively.

The higher mobility values in healthy subjects may reflect a more dynamic and adaptive cardiac response, while lower mobility in VHD patients could indicate a more rigid or dysfunctional cardiac system.

Table 3 presents the results of the two-sample t-test for the Hjorth parameters between healthy volunteers and patients with VHD. We did not observe significant differences in complexity for all signals and activity in SCG signals and significant differences in mobility for all signals and activity for ECG and GCG signals in healthy and patients with VHD.

Significant differences in mobility across all three signal modalities and activity suggest that these Hjorth parameters may be particularly sensitive to the physiological alterations induced by VHD; significant differences in activity observed in ECG and GCG signals suggest the impact of VHD on that the power distribution of these signals. Complexity did not exhibit significant differences in any of the three modalities, suggesting that the structural characteristics of these signals remain relatively stable between healthy population and patients with VHD.

4 Discussion

This study examined differences in Hjorth parameters—activity, mobility, and complexity—between healthy individuals and patients with valvular heart disease (VHD) using ECG, SCG, and GCG signals. Significant differences in mobility for all signals and in activity for ECG and GCG highlight their potential in distinguishing VHD patients.

Tab. 1: Descriptive statistics of Hjorth parameters for healthy population

Parameter	Signal	Mean	SD	Min	Median	Max
Activity	ECG	11467182.4921	25360063.0238	736753.2940	4636847.7545	136972014.7870
	SCG	0.1947	1.0309	0.0003	0.0007	5.5549
	GCG	255.9769	533.6307	0.3238	1.4343	2104.4641
Mobility	ECG	295.3352	371.9962	7.9730	95.1149	1219.1348
	SCG	446.7010	132.3680	4.6141	462.2141	672.8210
	GCG	183.3429	75.0929	86.8514	179.3353	364.0252
Complexity	ECG	23.2124	33.4031	1.2510	14.3848	169.5771
	SCG	12.3525	51.2209	1.5364	2.7801	278.6242
	GCG	6.5999	2.0022	3.4504	6.4537	10.4357

Tab. 2: Descriptive statistics of Hjorth parameters for patients with VHD

Parameter	Signal	Mean	SD	Min	Median	Max
Activity	ECG	2.8472	2.1998	0.1135	3.0508	10.2434
	SCG	0.0456	0.1974	0.0008	0.0032	1.0886
	GCG	1.3208	3.4477	0.0355	0.4899	19.3464
Mobility	ECG	15.4448	13.3489	3.7945	12.7443	80.3734
	SCG	117.2586	66.3115	8.4722	139.5536	200.3145
	GCG	68.2548	27.5149	28.7723	63.0505	182.2460
Complexity	ECG	17.5040	12.3015	2.2444	12.6133	58.1646
	SCG	5.5335	5.6031	1.9994	2.4421	27.9164
	GCG	5.9549	1.6792	2.3420	6.2102	11.1111

Tab. 3: Results of the two-sample t-test. Bold p-values indicate statistical significance.

Signal	Activity	Mobility	Complexity
ECG	**0.0016**	**0.0001**	0.3843
SCG	0.4402	**<0.0001**	0.4717
GCG	**0.0114**	**<0.0001**	0.1848

Differences in mobility suggest sensitivity to VHD-induced physiological changes, with higher values in healthy subjects indicating better adaptability [3, 6]. Altered activity in ECG and GCG signals supports findings of disrupted cardiac function in VHD [5]. The lack of significant differences in complexity indicates relative signal stability, contrasting previous findings in atrial fibrillation or heart failure [13]. The discrepancy may be due to differences in patient cohorts, data acquisition methods, or the specific nature of valvular dysfunction compared to other cardiac pathologies.

The findings suggest Hjorth parameters, especially mobility, as useful non-invasive markers for VHD assessment. Further validation in larger, more diverse datasets and clinical applications would be needed [10, 11].

5 Conclusion

Hjorth parameters, particularly mobility, can be used to differentiate VHD patients from healthy individuals using ECG, SCG, and GCG signals. activity also showed differences, while complexity remained unchanged.

This study supports the potential of signal-based markers for wearable cardiac monitoring. Future research should focus on larger and more diverse datasets, machine learning-based classification, and clinical integration to improve cardiac diagnostics.

Author Statement

Research funding: The author state no funding involved. Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: Not applicable—The research was based on publicly available data sets.

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