**Development and Comparative Analysis of Heart Rate Variability Metrics Across Activities in Healthy Individuals and Heart Failure Patients for Enhanced Remote Monitoring Systems**

This project focuses on using the Shimmers sensor to develop and compare Heart Rate Variability (HRV) metrics in both healthy individuals and heart failure patients across a spectrum of activities, including rest, mild, moderate, and stress-inducing situations. The aim is to enhance the accuracy and effectiveness of remote health monitoring for heart conditions by providing a detailed understanding of the differences in HRV measures between these two groups during various physical activities. This insight is vital for reducing hospital readmission rates, improving patient care, and enhancing health outcomes. By identifying variability and patterns in HRV in response to different physical and mental stressors, healthcare professionals can gain valuable knowledge for early detection of potential heart health exacerbations, enabling personalized treatment plans and facilitating timely medical interventions.

Motivation

The motivation for this project is rooted in the urgent need to improve remote health monitoring for heart condition patients, aiming to address the high rates of hospitalization and readmission associated with heart failure. Heart Rate Variability (HRV) analysis through wearable technology offers a promising solution by providing detailed insights into the autonomic nervous system's function and overall heart health. This dynamic approach to monitoring heart health can enable early detection of potential issues, allowing for timely intervention and personalized care plans.

Additionally, the recent shift towards telehealth, accelerated by the COVID-19 pandemic, highlights the importance of reliable remote monitoring technologies. By comparing HRV metrics across various activities in both healthy individuals and heart failure patients, this project seeks to enhance the accuracy and efficacy of remote health monitoring systems. The goal is to reduce hospital readmissions, improve patient outcomes, and support the ongoing evolution of cardiac care through innovative technological solutions.

Objectives

* To understand how HRV metrics vary across different activities (resting, walking, jogging, mentally induced stress) in healthy individuals.
* To develop a methodology for comparing HRV metrics that can later be applied to heart failure patients, enabling early detection of health issues.
* To explore the relationship between physical activity levels and HRV metrics to gain insights into the impact of stressors on heart health.
* To employ machine learning techniques for pattern recognition in HRV data, facilitating the identification of health-related patterns.

METHODOLOGY

To deepen the understanding of the methodology employed in this project for analyzing Heart Rate Variability (HRV) in relation to different levels of physical and mental activity, we'll elaborate on the data collection and analysis approaches mentioned.

The project utilized HRV and accelerometer data collected from wearable Shimmer sensors on two healthy individuals, segmented into four activities: resting, walking, jogging, and mentally induced stress.

DATA COLLECTION

Data Collection

The data collection phase was meticulously designed to ensure a comprehensive capture of physiological responses under varying conditions. The Shimmer sensors, known for their reliability in capturing biometric data, were employed to monitor two key types of data from each participant:

**HRV Data:** This primary dataset includes time-domain, frequency-domain, and non-linear HRV metrics. These metrics are crucial for assessing the autonomic nervous system's regulation of the heart rate during different activities.

**Accelerometer Data:** This data helps in categorizing the intensity of physical activity. It was continuously recorded to classify the participants' movements into four predefined categories: resting, walking, jogging, and situations that induce mental stress (e.g., performing complex mental arithmetic).

Each participant wore the Shimmer sensor continuously, ensuring that data from a full spectrum of daily activities were captured. Activities were categorized based on accelerometer readings, which were then correlated with HRV data to analyze the physiological impacts of each activity type.

Data Analysis Approach

The analysis phase was structured into several layers to systematically extract and interpret the wealth of data collected:

HRV Metric Analysis: HRV metrics for each activity were analyzed to understand physiological responses to different stress levels.

Comparative Analysis

While a direct comparison with heart failure patients wasn't within the scope of this initial project, establishing a comprehensive baseline of HRV variability and patterns in healthy individuals sets a critical foundation. This baseline is essential to show the range for normal operations and identifying that outside this ranges, abnormality occurs hence, aiming to distinguish between physiological responses in healthy individuals versus those with heart failure.

Pattern Recognition

The project laid the groundwork for employing machine learning algorithms to classify HRV data by activity type. Feature selection involved identifying which HRV metrics significantly change with different types of physical and mental stress.

Preliminary models, such as decision trees, support vector machines (SVM), and neural networks, were evaluated for their ability to accurately classify activities based on HRV and accelerometer data.

Correlation Analysis

A detailed correlation analysis was conducted to explore the relationship between specific HRV metrics and the intensity of activities. This involved statistical methods to identify significant correlations, facilitating a deeper understanding of how different types of activities impact heart health.

The impact of mentally induced stress versus physical activity on HRV metrics was particularly scrutinized to discern the nuanced effects of mental stress compared to physical exertion.

RESULTS AND DISCUSSION

**HRV Variability Across Activities**

The analysis revealed distinct patterns in HRV metrics corresponding to different activities, with physical activities generally showing increased HRV compared to resting. This aligns with physiological expectations and highlights the importance of contextualizing HRV data within specific activity types.

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The box plots above display the variability in HRV (Heart Rate Variability) metrics across different activities (Resting, Walking, Jogging, Mentally Induced Stress) for both the female and male participants. These plots offer a visual representation of the spread and distribution of HRV values during each activity, highlighting:

Median HRV Rates: Indicated by the line within each box, showing the central tendency of HRV for each activity.

Variability and Range: The length of each box and the whiskers indicate the spread and range of HRV values, with longer boxes and whiskers signifying greater variability.

Outliers: Points outside the whiskers represent outlier HRV values, which could be of interest when monitoring for abnormal heart function.

**Observations and Implications for Remote Monitoring:**

Activity Impact on HRV: The plots demonstrate how HRV varies with activity type, with physical activities like walking and jogging generally showing higher variability compared to resting and mentally induced stress. This underscores the importance of activity context in interpreting HRV data for health monitoring.

Individual Differences: There are notable differences between the participants in terms of HRV response to the same activities, which emphasizes the need for personalized baselines in remote health monitoring systems.

Potential Alert Thresholds: The variability observed during each activity could inform the setting of dynamic alert thresholds in a monitoring system. For example, HRV values consistently below the lower quartile during resting could trigger an alert for further health assessment.

**Statistical Insights**

Average HRV rates and standard deviations were calculated for each activity, illustrating the variability and potential stress response indicators. These statistical insights provide a quantitative basis for understanding HRV dynamics and their implications for heart health.

Female Participant:

Resting: Avg = 81.53 BPM, Std Dev = 2.68

Walking: Avg = 96.11 BPM, Std Dev = 4.42

Jogging: Avg = 101.44 BPM, Std Dev = 9.23

Mentally Induced Stress: Avg = 98.71 BPM, Std Dev = 11.39

Male Participant:

Resting: Avg = 71.94 BPM, Std Dev = 4.87

Walking: Avg = 86.71 BPM, Std Dev = 6.63

Jogging: Avg = 115.37 BPM, Std Dev = 12.78

Mentally Induced Stress: Avg = 110.00 BPM, Std Dev = 11.07

These results show clear variations in HRV metrics across different activities, with a general trend of increased HRV during physical activities (walking, jogging) compared to resting for both participants. The mentally induced stress also shows an elevated HRV compared to resting, indicating a physiological response to mental stress.

Notably, the male participant shows a higher increase in HRV during jogging compared to the female participant, which might reflect individual differences in physical condition or response to exercise.

**Machine Learning and Pattern Recognition**

This involves using machine learning to identify complex patterns in HRV data (and possibly other physiological parameters) that could indicate health issues beyond simple threshold breaches. This approach can uncover subtle changes in HRV patterns that precede health problems, potentially offering even earlier detection capabilities.

In the project, a decision tree classifier was utilized to analyze HRV and accelerometer data from wearable sensors to classify activities into categories such as resting, walking, and jogging. This classifier sorts data based on movement intensity and HRV patterns specific to each activity.

BELOW IS THE CLASSIFICATION REPORT FOR THE DECISION TREE CLASSIFIER

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Subsequently, 'normal' HRV ranges were determined for each activity type, using healthy individuals' data as a baseline. These ranges capture the expected HRV responses for different activities.

A binary classifier then used these HRV ranges to monitor for deviations, flagging data that fell outside the normal as potential health issues. This step is crucial for early detection of health problems, as it identifies subtle physiological changes that could indicate risks before they become acute.

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This two-tiered machine learning approach supports the project's goal to improve remote health monitoring by providing a nuanced analysis of HRV data, enabling early intervention and personalized healthcare for heart condition patients.

CORRELATION ANALYSIS

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* Heart Rate Variability (HRV) data exhibited low to no linear correlation with the accelerometer data across the X, Y, and Z axes, indicating that HRV measures may operate independently of movement captured by these axes.
* The calculated acceleration magnitude showed a moderate positive correlation with the X and Y axes but less so with the Z-axis. This suggests that acceleration in the horizontal plane (X and Y) contributes more significantly to the overall magnitude of movement than vertical movement (Z).
* Inter-axis correlations between accelerometer readings were observed, with the strongest relationship between the Y and Z axes, implying that physical activities captured often involved combined movements in these planes.

These illustrate the distinct and sometimes independent behavior of HRV metrics compared to physical motion metrics, thereby enhancing the ability to discern physiological changes from activity levels.

**Implications for Remote Health Monitoring**

The findings underscore the potential of using HRV metrics and machine learning for advanced health monitoring. Personalized alert thresholds, based on an individual's activity context and baseline HRV data, could significantly improve early detection of heart health issues.

**Conclusions and Future Directions**

This project has demonstrated the feasibility and importance of analyzing HRV metrics across various activities to enhance remote health monitoring. Future work should focus on:

* Refining machine learning models for more accurate pattern recognition and health issue detection.
* Exploring the integration of additional physiological parameters and contextual data for a holistic health monitoring approach