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Demographic Influences on Human Motion Patterns: A Feature-Based Study

Sandeep Gupta[1], Vibha Aggarwal[2] (Corresponding author), Manjeet Singh Patterh[3], Lovepreet Singh[4]
[1]College of Engineering and Management, Punjabi University Neighbourhood Campus, Punjab, India
[2]University College, Barnala, Punjab, India
[3]Department of Electronics and Communication Engineering, Punjabi University, Patiala, Punjab, India
[4]University College, Barnala, Punjab, India

Abstract: This study investigates the intricate relationships between demographic factors and human motion patterns, employing a feature-based analysis to find variations across different population segments. By examining a diverse range of demographic variables, such as age, gender, socioeconomic status, and cultural background, we aim to identify how these factors shape and influence human movement characteristics. For this work, data is collected through wearable sensors and features are extracted form data. To find the outcomes of this study, statistical analysis was conducted to predict the effect of demographic factors on gender basis. The aim of this study is to provide a comprehensive understanding of the demographic influences on human motion, which can have implications for various fields, including urban planning, healthcare, and security.
Keywords: Human motion patterns, wearable Sensors, healthcare, ANOVA, statistical analysis

I. INTRODUCTION

Human motion, a fundamental aspect of daily life, is intricately linked to an individual's identity and environment. The way people move, their gait, speed, and spatial trajectories, reflects a complex interplay of biological, psychological, and social factors. Understanding the nuances of human motion patterns is crucial for various applications, ranging from clinical diagnosis and rehabilitation to urban planning and security systems. Demographic factors, such as age, gender, socioeconomic status, and cultural background, play a significant role in shaping these motion patterns. Older individuals in higher socioeconomic positions tend to maintain high levels of physical activity, while those in lower socioeconomic positions are more prone to inactivity [1]. The study of human motion patterns has garnered considerable attention across diverse fields, ranging from robotics and surveillance to healthcare and urban planning [2] [3]. Understanding and modeling these patterns is crucial for a multitude of applications, including the design of efficient pedestrian facilities, the development of personalized rehabilitation programs, and the creation of socially aware robots [4-6]. Human mobility patterns offer insights into the driving factors of society, as many facets of life are intertwined with these patterns [7]. The intricacies of human movement can be unveiled through careful analysis of the factors shaping them. By using inertial sensors, it is possible to detect and characterize specific movements and register variations in the clinic and monitor activities of daily living [8]. Classifying human physical activity through automated systems holds immense promise for healthcare monitoring and advanced human-machine interfaces, encompassing static postures like standing and sitting, as well as dynamic motions such as walking, running, and stair climbing [9]. The complexity of human motion arises from the intricate interplay of numerous factors, including biomechanics, environmental constraints, and individual characteristics. Demographic variables, such as age, gender, socioeconomic status, and cultural background, exert a profound influence on how individuals move and interact with their surroundings [10]. Understanding the variables involved with movement is difficult to investigate quantitatively [11]. While gait movements have been a primary focus with advanced tools developed to measure movement parameters and reaction forces, the study of upper extremities, known for variable and adaptive manipulation, presents considerably more complexity. The analysis of human movement is critical to detecting physiological and pathological changes, and it is becoming more valuable in clinical application [12].

II. BACKGROUND AND RELATED WORK

Existing research demonstrates that human motion is influenced by a complex interplay of factors, including demographic characteristics, environmental conditions, and individual preferences. For example, older adults may exhibit slower gait speeds and shorter stride lengths compared to younger individuals, while individuals from different cultural backgrounds may have distinct patterns of body language and nonverbal communication [13].

Analysing movement data and gait biomechanics through wearable sensors, depth cameras, and 3D motion tracking systems, is increasingly common in fall risk assessment among older adults [14]. Understanding the nuanced interplay of factors influencing human motion patterns is imperative for various applications, spanning from healthcare monitoring to advanced human-machine interfaces that incorporate static postures and dynamic motions [15].

A quantitative gait feature assessment is crucial for identifying gait patterns and characteristics in clinical settings, facilitating effective treatment and predictive outcome assessment [16]. Wearable sensor technology, coupled with seamless data exchange for human motion detection, holds immense potential for smart healthcare application. A continuous monitoring of gait and posture disorders is essential, offering valuable insights into underlying pathologies and recovery progress across diverse medical conditions [17]. Lower-limb rehabilitation robotics has emerged as a promising tool for restoring efficient bipedal gait, highlighting the significance of human-machine interfaces in achieving dexterous and accurate manipulation for ambulation-impaired patients. Profound proficiency in artificial intelligence technology has been explored in almost every field and is improving assessments while becoming more trustworthy [18]. Gait analysis has found applications in sports, rehabilitation, and health diagnostics, identifying faults in athlete performances, monitoring patient healing progress, and discriminating between asymptomatic subjects and patients with medial knee osteoarthritis [19]. A comparable statistical analysis was performed on biomedical signals, including fPCG, and EHG, to predict normal and emergency situations by acquiring these signals through non-invasive methods [20-22].

III. METHODOLOGY

For the work, 32 healthy participants men and 19 women - who were of ages ranging between 23 and 52 years. There were 31 right-handed participants; one individual identified themselves as ambidextrous [23]. All participants then asked to execute a series of prescribed movements designed to capture a wide range of motion patterns such as walking, running, and stair climbing, as well as sit to stand transfers. The data was collected simultaneously form left wrist (lw), left hip (lh), left ankle (la) and right ankle (ra) at a frequency of 100 Hz. The data was processed to extract relevant features, including gait speed, stride length, joint angles, and trunk sway, which were normalized to account for differences in body size. Feature extraction plays a critical role in identifying salient characteristics within human motion data, enabling subsequent analysis and interpretation of underlying patterns. Feature selection techniques are also used to choose the most relevant features for modelling and analysis and reduce dimensionality and improve model performance.

IV. RESULTS AND DISCUSSIONS

Figure 1 shows the box plots for statical analysis of data collected from different body parts for both male and female participants, and calculated results indicating that male have high median values then female. Outliers confirmed that some females have exceptionally high values as compared to their counterparts but those females are less in number.

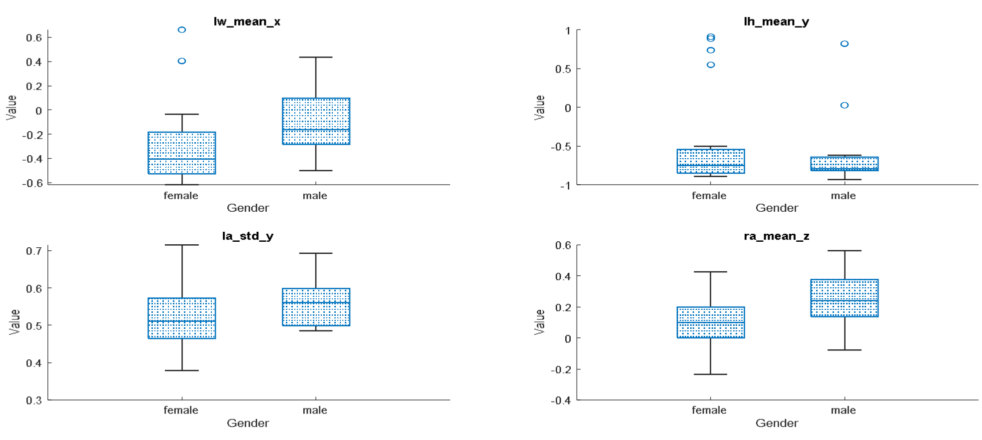

Figure 1: Box plot-based feature comparison on gender basis

Figure 2 shows the box plots for statical analysis of data collected from different body parts for both male and female participants, on age basis, and obtained results confirming that young persons have high median values and high variations in left hip and ankle motion. The middle age group persons have tight interquartile range (IQR) except left wrist motion. Old age persons due to age factor have very tight IQR for all body motions.

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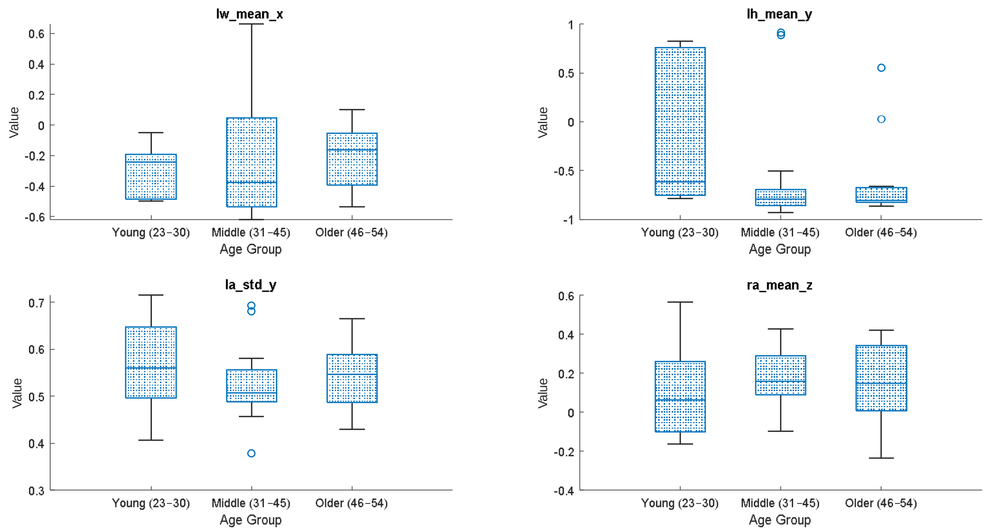

Figure 2: Box plot-based feature comparison on age basis

The ANOVA test conducted on different age groups show non-significant mean and standard deviation values as 0.8469, 0.2721, 0.6373 and 0.7666 for left wrist, left hip, left ankle and right ankle respectively. Figure 3 shows the comparison of motion feature for both male and female participants.

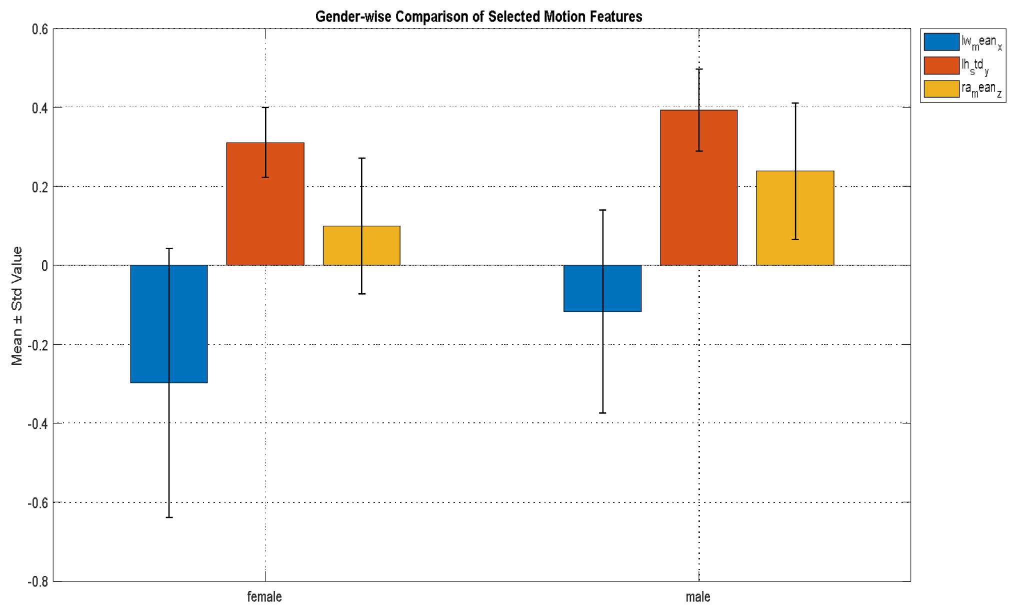

Figure 3: Gender wise comparison of selected motion features

V. CONCLUSION

This work is used to assess the effect of demographic factors on motion features and the statistical analysis contribute to establish the relation between motion feature on two constraints age and gender. The results indicate the clear distinction in motion features for male and female participants. Similarly, when compared on age bases for young, middle and old age participants, the results show clear difference in motion features. In future, work can be extended to establish the similar relations for different races and further more parameters and tests can be included to make the system more predictable.

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