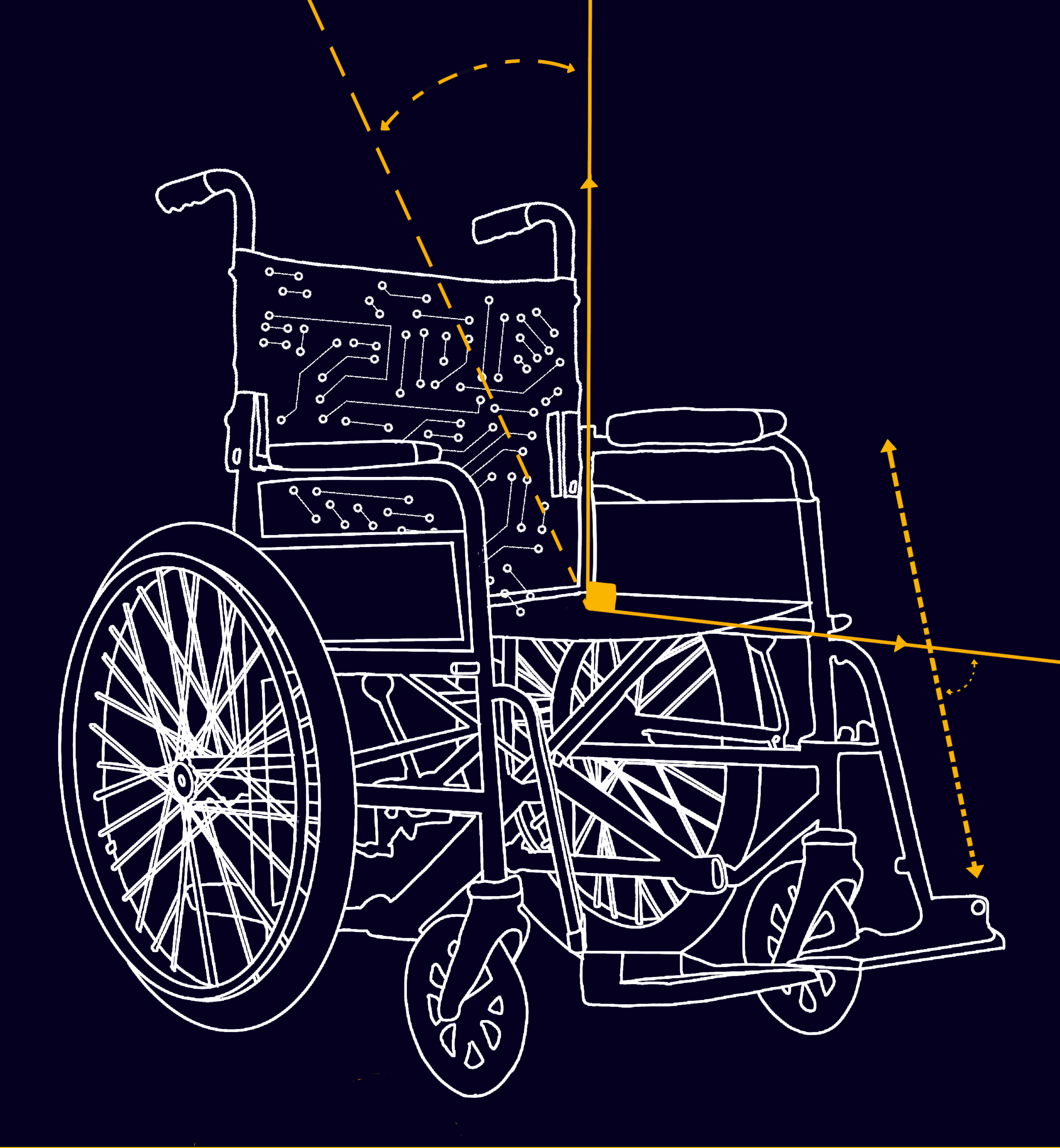

A Day in a Wheelchair

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MASTER THESIS

A Day on a Wheelchair

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"*The benefits of technology are not a privilige of some, they are a right of all.*"

DELFT UNIVERSITY OF TECHNOLOGY

Abstract

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Master of Science

A Day on a Wheelchair

by Dhaval SHAH

Advances in sensing and machine learning technologies give rise to personal health coaches that monitor human activities and support healthy behaviour. In this context, wheelchair users can benefit from such technologies as they often suffer from physical ailments due to insufficient or over activity, prolonged improper posture and lack of postural changes. While sitting posture is a well-studied area, current works focus on the recognition of less frequent postures and miss important postures such as slouching and pelvic postures. The benefits gained from activity tracking also remain restricted to able bodied individuals. In this thesis we demonstrate an end-to-end, multimodal, wheelchair sitting posture and activity monitoring system facilitating just-in-time feedback on postural changes. By using an earable to monitor activity and head posture with a complementary filter and performing classification using Force Sensitive Resistors, we show faster and more precise recognition of relevant postures and activity.

Acknowledgements

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Finally, I would like to thank my family, who despite not being here physically, have always supported me in spirit.

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Chapter 1

Introduction

For a person on a wheelchair, a day is both guided and restricted by being in the wheelchair all the time. They do engage in regular activities such as eating, reading, etc, but all that and more happens within the confines of the wheelchair. It then poses the question that if the wheelchair is such an important part of their time spent awake, would providing a wheelchair more capable than just taking them around, help such people to lead better lives.

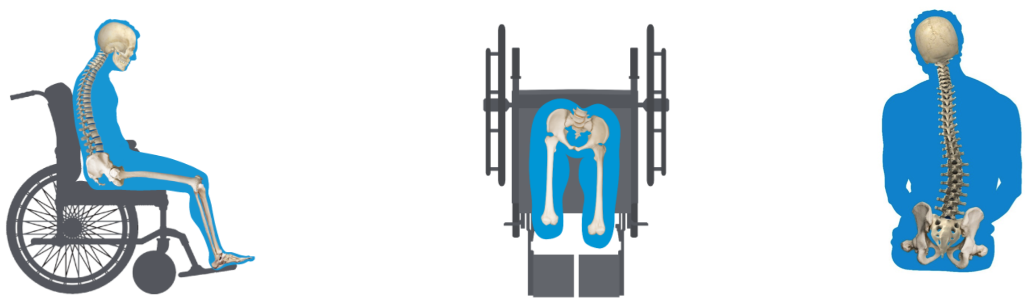
The rising population of the elderly and disabled warrants greater scrutiny towards the causes of discomfort for such people and suggests strategies to alleviate them in a pre-emptive manner. A large portion of this population remains confined to a wheelchair continuously for long periods of time. It was estimated by the World Health Organization that about 65 million people were confined to a wheelchair due to disability in 2010[1].

Low Back Pain(LBP) is faced by between 14% and 38% of office workers in Thailand, Greece and Denmark[2][3][4][5]. Sitting in poor postures for an extended period of time has considerably increased the risk of experiencing LBP, the ill effects of which include large and infrequent, over subtle and regular spinal movements and discomfort in the lower back[5]. It cost the Netherlands over €3.5 billion in 2007[6].

Common postural inadequacies found among wheelchair users are[7]:

1. Kyphotic Slouching(Figure 1.1a)
2. Pelvic Obliquity (Figure 1.1c)
3. Pelvic Rotation (Figure 1.1b)

Pelvic Obliquity and Rotation lead to uneven weight distribution on the seat and which may cause pressure ulcers over extended periods of time[7].



(A) Kyphotic Slouching

(B) Pelvic Rotation

(C) Pelvic Obliquity

FIGURE 1.1: Common postural deformities amongst wheelchair users[8]

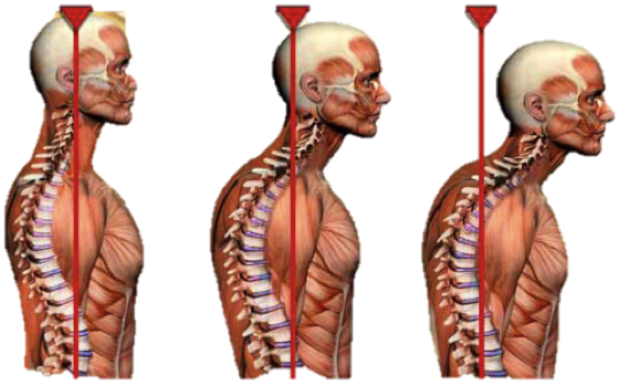


FIGURE 1.2: Forward Head Posture[9]

Forward Head Posture(FHP)(Figure 1.2) has been credited to be the predominant cause of neck pain among adults. This posture is common amongst the disabled and the elderly due to reduced neck and shoulder movement, and also due to habitual convenience guided behaviour, having to pull their face forward to eat instead of lifting their arms fully due to weak arms. Other reasons include having to crane the neck forward to read and watch television due to weakened eyesight.

Wheelchair users also remain victims to reduced physical activity. A majority of such population does not meet the minimum physical activity recommended for health and disease prevention [10]. Much of their daily activities, such as reading, eating, talking etc classify as sedentary behaviour and mostly takes place indoors. Physical Activity Guidelines for American Committee(PAGAC)[11] recommends between 500 and 1000 Metabolic Equivalent of Tasks(METs) per week for good health, whereas above mentioned activities cost less than 1.5MET each.

Samuelsson et al.[12] posit that wheelchair users could minimize LBP by modifying their sitting posture. Recognition of above mentioned postures may also help in preventing pressure ulcers and chronic neck pains. Among patients with C5-C6 tetraplegia, Bolin et al. [13] perform intervention when bad posture is identified in patients and notice improvement in their subjects' problems caused by sitting positions. Tracking of a users activities may aid in designing solutions to bridge the gap between existing and the recommended activity quota. It may also be the case some times that a user exerts more force to propel himself than what is recommended. This may also be eventually measured following accurate activity tracking.

Sensors present in devices used in everyday life are increasingly being used to capture Activities of Daily Life(ADL) and have given rise to increased research and development in Ambient Assisted Living(AAL), eg: sensors in mobile phones, wrist-watches etc[14]. AAL is likely to provide independence to the elderly in the face of rising healthcare costs[15].

However, despite the fact that wheelchair users' posture and inactivity can lead to serious health consequences, few self-tracking opportunities are currently available for such population. With the population of wheelchair users is growing worldwide, it becomes urgent to design supportive technologies for them to improve their well being. Further in this document, a system is proposed. The system exploits the concept of multimodality by using Force Sensitive Resistors(FSR) placed on a wheelchair and eSense earable, developed by Nokia Bell Labs, to identify their postural and activity behaviour, and suggests a rudimentary strategy to inform them of the same. FSR's along with a KNN classifier is used to identify the thoracic and pelvic postures, a complementary filter uses earable sensors to identify FHP, and accelerometer data is analyzed to record physical movement.

In this thesis, we first take a look at the existing systems designed to take care of the problems outlined above, and if they are sufficient for the same in Chapter 2. We also explore theory necessary to design a system addressing the above problems. We finally come up with a hypothesis and set concrete goals for the same. In Chapter 3 we take a look at the individual components required to build the proposed system and as to how they work together. In Chapter 4 we compare our system with the other existing systems out there, while highlighting its strengths and weaknesses. Towards the end, Chapter 5 provides a holistic end to the contributions of this thesis, while Chapter 6 provides future directions that could be taken from this work.

Chapter 2

Literature Review

In this chapter, we look at existing systems that solve some (or all) of the problems that we identify in Chapter 1. We then critically analyse if these systems are sufficient and accordingly make decisions for features and components for our system. The review also eventually helps us compare to already existing systems and evaluate if we are indeed able to offer a better alternative to the existing systems.

2.1 Posture Recognition in Literature

Posture recognition is not a novel field of study. Many implementations of systems exist already that measure recognize postures with different sensors. Given below is a brief overview of existing systems.

2.1.1 Body Posture and Activity Recognition

Body posture systems are able to recognize the posture of the entire body. Typically this is possible by measuring movements of all moving body parts in the most accurate systems, or by measuring some moving parts while making reasonable interpolations for others, resulting in lower accuracy. The kind of systems can be widely classified into,

1. Vision Based Systems
2. Wearable Systems

Vision Based Systems

These systems measure the full range of motion of all moving parts. This movement is reconstructed based on measurements and postures are identified from the reconstruction. The position of cameras is of paramount importance in all vision based systems. Professional motion capture systems such as Qualisys[16] and Vicon[17] use multiple infrared cameras with reflective markers placed on subjects under observation, and have set the standard for accurate posture estimation. These are typically used for sports analysis and validating research. Other purpose built systems however, may function with fewer and lower resolution cameras. [18] uses a single camera to separate the body from the environment and then identify five significant points on the body for 2D posture estimation. [19] uses three cameras in a car to infer the driver's upper body posture. None of them state the accuracy of their system.

Principally, all vision based systems use strategically places cameras to record body movement in a large area These cameras are usually equipped with wide angle lenses. A relatively new addition to the system are time of flight cameras.

Wearable Posture Recognition

The core principle to be followed while positioning sensors is that they should be securely fitted to avoid relative any movement with respect to the body. Gemperle et al.[20] position sensors at the upper body collar area, rear of upper arm, front and rear of the chest and waist. Only in [21] is an example of placing the accelerometers behind the ears seen for fall detection.

There are two predominant methods to achieve posture and activity detection using wearable sensors. The more popular method uses machine learning and classification algorithms as seen in [22]. They use a random forest classification model to identify postures first with just an accelerometer and then with accelerometer, gyroscope and magnetometer combined. They are able to achieve between 69% and 95% accuracy in the first case and between 84% and 95% in the second case. [23] also uses classification using 4 accelerometers on the upper arm, ankle, thigh and the waist. They use a decision tree classification algorithm and achieve 99.4% accuracy.

[24] proposes a system using IMU's placed on the arm. Here they compare results achieved using both an EKF and a complementary filter and conclude that the errors generated by the EKF are lower. [25] proposes an EKF based system to estimate both gait and posture. They use multiple IMU's placed throughout the body and make a simple classification between walking and sitting and then run an EKF to identify the dynamic state.

Both technologies individually have reached sufficient maturity. Commercial vision based motion capture products like Microsoft Kinect and wearable posture correction products like the Upright Go are cheaply available and highly accurate. Research is now focused on smarter materials such as in [26], which focuses on smart garments that can estimate posture.

2.1.2 Seated Posture Recognition

Recognizing seated posture typically involves the measuring pressure distribution distribution of the user on the seat and the back rest of the chair using Force Sensitive Resistors(FSR) [27][28] or using pressure mats[29]. A brief adaptation of the table from [28] is presented in Table 2.1 to provide an overview of existing methods. Recently, the system in [30] and the LifeChair [31] have been developed, where the former uses a load cell arrangement on the seat whereas the latter uses a sensor array cushion on the back. Interestingly, the latter is capable of identifying slouching. Almost all implementations record an accuracy of >95% and identify a similar set of postures namely (1) Seated Properly, (2) Leaning Forward, (3) Leaning Sideward and few other ancilliary postures. The direction of research in this field has been largely towards optimising sensor placement to reduce to number of sensors required.

2.2 Activity Recognition

According to the Vandrico database[32], 40% of all wearable devices are wrist worn. This number goes higher if only activity or fitness trackers are considered. [33] proposes a solution to monitor activity of wheelchair users using a wrist worn wearble device. This trend is carried forward with popular devices such as the Fitbit Flex, the Apple Watch, and similar trackers. The activities that are recognized are:

1. No Movement
2. Sedentary Activities
3. Self Propulsion
4. External Pushing

We find this exact set of activities relevant to our system as well, since the goal is to monitor energy expenditure. There is already available literature on the energy expenditure of various sedentary and physical activities[11]. Identification of the above activities can help in getting an estimate of the energy spent by the user.

Commercially available trackers are highly accurate to monitor activity for able bodied individuals as they count the steps taken. However, wheelchair users do not take steps and hence these devices do not meet the needs of wheelchair users in particular[34]. The Apple Watch in particular, in its most recent iteration, Series 4 has some features for wheelchair users, such as calories burned and a *"Time to Roll"*, which indicates users to move.

Another class of devices exclusively manufactured for wheelchair users are those that attach onto the wheelchair itself, such as SmartWheels[35] and Freewheel[36]. However, these are all very expensive and require technical expertise for maximum utilization. These devices are more suited towards hospitals and rehabilitation centres but not for personal use. All of the above devices use accelerometers to track movements. With the population of wheelchair users steadily rising, it presents a need to develop self-tracking technologies for personal use.

2.3 Drawbacks of Existing Systems

Vision based systems require large areas where cameras in best case have unrestricted field of view to the subject. This is not possible in a day to day setting for any person, let alone wheelchair users.

Wearable systems are much more feasible for activity tracking. The most common implementations require at minimum, multiple optimally placed IMU's to achieve good accuracy. Popular choices for sensor placement are along the back due to its high frequency of movement and its contribution to determining the whole body posture, i.e. the posture of the back plays the highest role over other body parts in determining the complete posture. This is followed by wearable belts housing IMU's around the waist due to its closeness to the body centre of mass. Both these choices are unfavourable to our context because of the uncomfortable sitting experience they are likely to create. These systems also require external help in wearing properly. This introduces dependence on other individuals diluting the value of a self tracking and makes their overall usefulness in day to day situations lesser.

Author	Sensor Type/ Number	Placement of Sensor	Type Of Posture	Classification Technique/ Method	Feedback	Accuracy
[29]	E-textile/ NA	Seat	Static	Gray scale image	No	85.9%
[38]	E-textile/ NA	Seat and Back	Static	Pressure mapping	No	N/A
[39]	E-textile/ NA	Seat and Back	Static	PCA, Grayscale image	No	96%
[40]	E-textile/ NA	Seat and Back	Static	Neural Network	No	87.6%
[41]	textile pressure sensor/ NA	Seat	Static	Neural Network	No	82%
[42]	Pressure Sensor/ 19	Seat and Back	Static	Logistic Regression	No	87%
[43]	Pressure Sensor/ 64	Seat	Static	SVM	No	98.9%
[29]	Sensor Array/ 64	Seat and Back	Static	Binary pressure distribution, Naive Bayes	No	82.3%
[44]	Sensor Array/ 64	Seat	Static	pressure mapping technology	No	N/A
[30]	Load Cells/ 4	Seat	Static	SVM	No	97.94%
[31]	Pressure Sensor/ 9	Back	Static	NA	Yes - Vibration	98.1%
[22]	IMU/ 3	Chest, Thigh, Ankle	Dynamic	Random Forest Classification	No	84%
[23]	Accelerometer/ 4	Arm, Thigh, Waist, Ankle	Dynamic	Random Forest, Decision Tree	No	99.4%
[24]	IMU	Arm	Dynamic	EKF, Complementary Filter	No	N/A
[25]	IMU/3	Waist, Thighs	Dynamic	EKF	No	100%

TABLE 2.1: Existing Posture Sensing Systems

In seated posture estimation systems, a near ceiling has been reached in terms of accuracy and sensor placement. This leads us to believe that pressure sensors are ideal to recognize seated posture. However, while these systems classify a large number of postures, a closer examination reveals that these postures (apart from proper sitting) are unlikely to occur during regular passage of time, i.e. a user is unlikely to lean forward unless it is necessary, making the utility of identifying such a posture marginal. Due to constant sitting, wheelchair users are much more likely to fall into postures such as slouching or hunching. Users also maintain improper pelvic postures for a long duration of time due to ill fitted wheelchairs. Although we could not find any literature on the average time a wheelchair bound person spend slouched or hunched, [37] records between 32% and 50% time of sitting is spent in the "risky slouch" position among office workers. Moreover existing implementations also almost exclusively focus on back posture and completely ignore pelvic postures, completely ignoring high frequency and high impact postures.

The lack of actuation for posture correction is also noticed in studied literature. While high accuracy is commendable, it ultimately does not translate to preventative or corrective measures for the users who are classified with having improper posture.

In terms of Activity Tracking, there is a unique situation. Not only do most existing products do not meet the needs of self tracking for wheelchair users, but newer technologies are not being developed at a speed matching the need of the consumer. The options which are available are either too expensive, or have a high barrier of entry, such as the technological learning curve that comes with owning an Apple Watch for the elderly. Such a learning curve has the possibility of alienating the users it tries to benefit. It is highly crucial to empower wheelchair users with self monitoring capabilities just as the general population has been. Such a feature could benefit almost everyone either to meet their activity quota or consciously not overstep it.

It is identified that there is higher utility in identifying intermediate postures such as slouching and pelvic postures due to their high impact and frequency. A system capable of performing such classification would indeed be novel. These postures should at best be added to the existing catalogue of postures that are possible to identify, or at worst completely replace them. FHP should be stressed upon as much as pelvic and back posture due to its equally harmful effects and regular occurrence. To be able to identify FHP, it is required to measure fine movements of the neck and the head.

It is also evident that IMU's prove to be deserving candidates to recognize dynamic movements of the body due to their high sensitivity. Moreover, accelerometers are almost exclusively the sensor of choice to identify activities. While additional body and pelvic postures may be sufficiently identified by just FSRs, to identify FHP and track activity we do need an accelerometer at least. Since we intend to supplement body posture with neck posture and recognize activity, it can be reasonably assumed that combining elements of both systems would provide optimal results. A one system solution for both these individual problems would in itself be unique, however using a smart device to achieve such functionality while it simultaneously fulfils its primary function would make the value proposition for the system higher. Finally, such a system would also be a unique combination of wearable smart devices, and near body sensors on a system built for personal use.

The needs that are identified to realize such a system are (1) Modality and multimodal interaction, (2) Sensor Fusion and (3) Intervention Strategy

2.4 Modality

From a scientific perspective, a “mode” refers to an input method. Concretely, systems that combine different natural input modalities to generate an output is known as a multimodal system [45]. Some examples of multimodal systems include their usage in biometrics [46][47][48], as well as in [49][50], where the focus is on combining speech and gestures. However, the increasing availability and accuracy of sensors, as well as a paradigm shift in research has led to innovation in other fields using multimodal sensing.

A key requirement to extract the most benefits out of all modalities is for them to be complementary to each other. This “Diversity” allows us to enhances the uses and insights beyond those achieved by a single modality [51]. The proposed system combines stationary sensors such as the FSR with dynamic sensors such as IMU, both of which provide complementing outputs, our system meets the requirements of a multimodal system.

2.5 Data Fusion

Data Fusion is a very broad domain and as such, has found some difficulty to maintain one definition. Attempts towards it have been made by [52] by defining it as combining two images to form a new image using some algorithm, or variations of a more general definition such as in [51][53] which is along the lines of data fusion being the analysis of several data sets such that different data sets can interact and inform one another. The U.S Department of Defense [54] defines it as “a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from multiple sources.” Despite the plethora of definitions, the general problem with multisensor fusion as quoted from [55] is:

> “How is it possible to observe a dynamical scene with a set of sensors by controlling their configuration, i.e. their sequencing, as well as the scheduling of the resources, be they directly attached to the sensor or centralized.”

To understand why we need data fusion, we take the example of accelerometer and gyroscope fusion for pose and orientation estimation in drones as well as humanoid robots. Accelerometer data is very noisy in the short term and susceptible to interference. Gyroscope on the other hand provides very accurate short term readings but tends to drift over a longer period of time due to the accumulation of angular velocity bias [56]. Combining the advantages and disadvantages of both accelerometers and gyroscopes makes tilt sensing extremely reliable and make a good argument on the necessity of sensor fusion. Kalman Filters [57] and Complementary Filters [51] remain the most popular methods to achieve this. Adding more sensors such as Magnetometers and GPS can make the system more capable and accurate.

Sensor fusion may be considered as a subset of data fusion. Data fusion may include any data set such as surveys and questionnaires in addition to sensory data, which when fused exclusively is called sensor fusion.

2.5.1 Joint Data Laboratories Model

The most widely accepted model for data fusion is the Joint Directors of Laboratories(JDL) data fusion process model [58] as shown in Figure 2.1. This model was designed in the

1980's with majorly military applications in mind. However, generalities in the model have been exploited through time to fit it to a multitude of cases. That, combined with a lack of overarching framework for sensor fusion makes it relevant to this day.

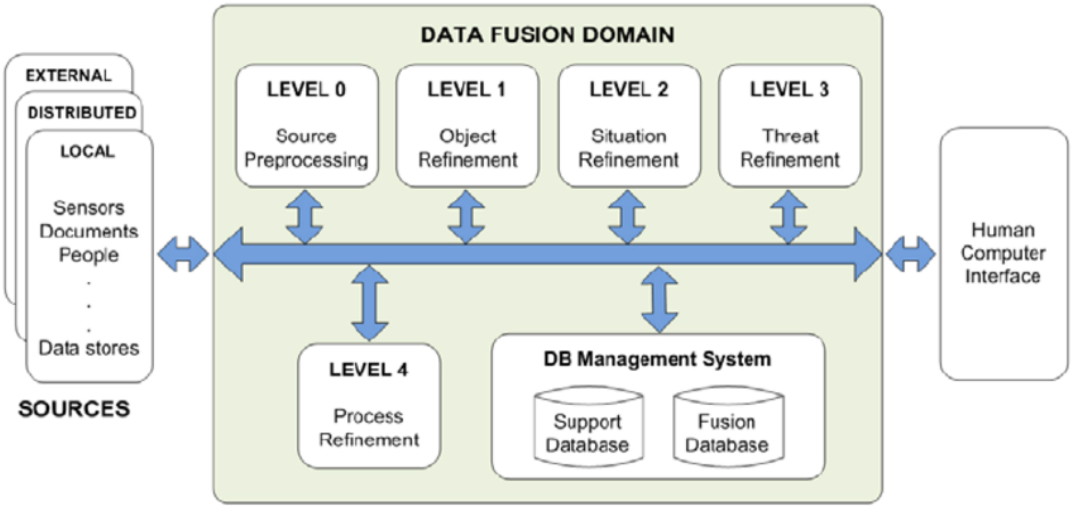


FIGURE 2.1: JDL Data Fusion Model[58]

Sources usually consist only of sensors, but may also have previously collected databases or environmental variables.

1. **Level 0(Source Preprocessing):** Level 0 processing involves any required pre-filtering to eliminate unnecessary noise/data. In the proposed system we only strip the packet headers, checksums and semantics from the generated data within the purview of Level 0 processing.

2. **Level 1(Object Refinement):** Level 1 combines parametric and identity data to achieve refined representation of targets [58]. This includes estimation of position, velocity, and identity of low-level identities or entities. It often involves classic target tracking and pattern recognition. The same trend is followed in the proposed system as we estimate the posture of the user, which is interpreted as identity of the target(user in our case) to fit into the model. Level 1 can be further broken down into:

    (a) Data Alignment

    (b) Data Association

    (c) Tracking

    (d) Identification

3. **Level 2(Situation Refinement):** Level 2 tries to decipher previously existing or develop new relationships among the objects being sensed. Feature extraction is quite a common manifestation of Level 2 fusion.

4. **Level 3(Threat Refinement):** Level 3 tries to extrapolate the existing sensor data and relationships into the future to pre-empt threats, vulnerabilities and opportunities.

5. **Level 4(Process Refinement):** Level 4 looks at data and predictions over a long time to suggest long term improvements.

Majority of the work in fusion systems is Level 1 fusion. It transforms data from multiple sources into one frame.

2.6 Sensor Fusion Methodologies

Sensor Fusion is usually classified into three stages: Signal, Attribute and Decision[59]. Fusion may occur at each of these stages individually, or in combination.

2.6.1 Machine Learning

Machine Learning concepts such as classifiers and pattern recognition are usually applied in fusion systems for object identity recognition and situation/threat refinement [60][61]. They usually perform fusion at the attribute or decision level. Classifiers are used for feature fusion, which falls under Data Alignment. Initial fusion occurs when similar values from different sensors, using tracker association from a close period of time are grouped using Naive Bayes or Decision Tree classifiers [62].

The authors of [63] come closest to the system proposed while using a machine learning based approach for sensor fusion. Using pressure sensing mats on a chair and cameras, non verbal cues are identified in real-time using Pattern Recognition implemented by a Support Vector Machine(SVM) algorithm. However, this requires more powerful hardware to fulfil the higher computation requirements.

A limitation of this approach, and of pattern recognition in general, is that the result usually depends more on the quality of features, rather than the method itself [58], which may get difficult in noisy environments.

2.6.2 Signal Processing

There are two major ways to approach data fusion from a signal processing perspective [64],

1. all sensor data is transmitted to a central location for processing
2. some of the processing is done at the sensor level for a more distributed system

Most natural signals are such that they contain most valuable information in few significant components [65]. This fact is exploited by the Kalman Filter, which is used for dynamic, low-level fusion[57].

Kalman Filters

Kalman filters remain method of choice for IMU fusion with other sensors, usually GPS for accurate location estimation [66][67]. Complementary filter however has much lower cost of computation, and provides results very close to that provided by a Kalman Filter. While a Kalman filter should be more accurate in theory, due to the higher number of tuning parameters, the chances of getting better results are reduced. This makes complementary filters more desirable for embedded applications [56].

The drawback for both Kalman and Complementary Filters is that they only give desired results on linear data. Since most natural processes are produce non-linear data, some modifications are required to the vanilla Kalman filter to produce favourable results or in case of complementary filters, some innaccuracy may be accounted to this fact.

Unscented Kalman Filters

Unscented Transformations are based on the intuition that it is easier to approximate a probability distribution than it is to approximate an arbitrary nonlinear function or transformation [68]. [69] provides a general algorithm for sigma point filters which can be implemented with an Unscented Kalman Filter(UKF). [70] presents the use of UKF in surgical tools for precision, wheres [71] uses for precise vehicle position and navigation, which is also an improvement over similar applications as mentioned above when implemented using regular Kalman Filters.

Extended Kalman Filters

Extended Kalman Filters(EKF) are the most common solution for nonlinear state estimation [72]. The basis for EKF is that they use linearized estimates of non linear data. [73] presents an EKF based navigation system for robots. This is also similar to other examples of applications we have seen using different filters.

[74] compares EKF and UKF for location tracking and finds out that in cases when GPS is added, the UKF performs slightly better, however without the GPS there is no difference. [75] makes a comparison in for head and head tracking. The authors conclude that the computational overhead associated with the UKF does not compensate for its marginal improvement in accuracy.

Other methods of fusion, such as an algebraic approach [76] and fuzzy logic [77] have been deliberately eliminated due to the nature of the data we receive from our system.

Current trend in the field leans towards the combination of the above stated methods, an architecture for which is suggested in [78], for the most efficient low-level fusion being done by Kalman-type filters, the mid-level fusion being done by unscented transformations, and high level classification and decision making is done by artificial intelligence and machine learning guided algorithms.

2.6.3 Sensor Fusion in Posture Detection

To accurately identify the posture of a seated person, it is important to accurately measure his translational velocities. This is not possible using only accelerometers due to their short term inaccuracy. Gyroscopes on the other hand are accurate in the short term. Fusion with gyroscope data from an IMU using Kalman filters or complementary filters gives us a slightly better estimate of the orientation. A solution to obtain dynamic posture estimation is to fuse IMU data and the Force Sensitive Resistors(FSR) to generate the angle of the user's back with the back rest. However, the problem we face here is that these filters perform well on linear data, which does not correspond to the data generated by the human body.

There is literature available as seen in [79] to fuse force data and IMU data to estimate body posture but they use load cells and torque meters. We were not able to find any existing literature for fusion of an array of FSR's with IMU's. The paper also uses exclusive and expensive hardware for real-time computation. Our goal remains to perform all calculation on cheap and commercially available hardware.

Three broad methods exist within literature as explained in earlier to estimate posture and movement using wearable sensors such as IMU's which generate non linear data. These are

1. EKF
2. UKF
3. Particle Filters

It is seen that EKF has lower computational overhead as compared to the other two methods. The downside of EKF is marginally lower accuracy. However this must also be compared against the appeal of complementary filters for embedded applications. For the purpose of this theses, we try both these methods.

2.7 Synchronization

An inherent problem when dealing with multiple modalities is to reconcile all those modalities to the same physical attribute. This becomes all the mode important in our systems as over different modalities, we are dealing with different transmission media bringing in uncertainty into our system. For this reason, we look at synchronization techniques going forward.

RBS[80] uses a reference broadcast message, in which a timestamp of the sender is not required. Instead, the receiver nodes use the time of arrival as a point of reference to compare their clocks. As opposed to synchronizing with one parent node, receivers synchronize themselves to each other. The broadcast message need not be a dedicated time-sync packet. In [81] as well, the receiver synchronizes with the sender with the broadcast. However, this broadcast message containing the sender's timestamp, which is the estimated global time. The receiver receives the broadcast message at its local time forming a global-local time pair, the difference of which gives the clock offset of the receiver.

Timing-sync Protocol for Sensor Networks(TPSN)[82] selects a single root(gateway between sensor network and external world) which remains fixed remains fixed. The network is divided into i levels and nodes in each level pass synchronization information to the i-1 level. This happens in a pairwise manner with a handshake mechanism between the sender and receiver in comparison to a receiver-receiver mechanism in [80]. The authors designed Time Diffusion synchronization Protocol in [83] to be automatically self configured and energy efficient. It synchronizes nodes to an equilibrium time. An initial broadcast is sent to begin synchronization by a master. A new master is randomly elected during at regular intervals. A Time Transition Algorithm synchronizes the network time with an equilibrium sensor time. Every diffused leader node diffuses timing information to its neighbour nodes.

2.7.1 Clock Drift

Oscillators in all receivers tick at marginally different rates. A single synchronization broadcast only provides instantaneous synchronization which drifts over time. Hence an estimation of clock skew, as well as regular re-synchronization needs to be performed to maintain desired level of precision.

Oscillators are modelled as having high short term frequency stability and ignore data more than a few minutes old in order to adjust for clock drift in [80]. Least squares linear regression is used to run a best fitting line on the differences of phase offsets of individual nodes. The slope of this line represents the clock skew. This analysis is carried out offline. [81] follows a similar modelling to [80], apart from that it runs online linear regression on the past 8 data points. Once an estimate is known, timely re-synchronization broadcasts are made to maintain desired precision. The precision of the system improves with the decrease in the re-synchronization interval. However, a trade-off must be made between the precision and the cost of computing.

Both [82] and [83] do not mention explicitly any mechanism to estimate clock drift. They also perform regular re-synchronization. The authors in [82] do find a worst case clock drift of $4.75\mu s/s$ experimentally and assert that TPSN performs twice better than [80] or the same clock drift.

Various protocols have been proposed above. However, we see that all of them are built for(and tested on) large scale infrastructure level WSN's and have microsecond level accuracy. The requirements for such networks is quite strict and the problem of synchronization is more challenging due to significant propagation delay incurred in covering the entire network, hence requiring sophisticated algorithms. Comparing these to the proposed system, it is evident that such level of sophistication is not necessary and might in fact, add significant overhead during run time. A much simpler synchronization method meeting our requirements of millisecond accuracy is presented in Chapter 3.

2.8 Decision

In 2.1 actuation was identified as a need of the realized system. However, before actual actuation, some intelligence must be applied on the output of the system, namely back and pelvic posture, neck posture, and activity. Conversations with personnel in assistance for wheelchair users at a rehabilitation centre provided insights as to slight movement every 15 minutes at a minimum for all wheelchair users. Activity tracking data over t can be used to compute MET's exercised by users and subsequently indicate the deficiency to meet the standards as outlined in Chapter 1. A tracking over longer periods can be done on the baseline head tilt. This may help in identifying onset of head ptosis and intervening with preventive measures on time.

A non-exhaustive study was also conducted on mediums of feedback. We explore haptic feedback mechanisms for the user. Two modes were considered:

1. Vibration
2. Electro Muscle Stimulation(EMS)

The authors of [84] conduct a study comparing both these types. They discover that users preferred EMS over vibration as it felt more realistic. Moreover, an initial prototype of the wheelchair containing vibration feedback was developed, and it was found to be unpleasant during experiments. Hence we suggest using EMS as the feedback delivery method.

2.9 Existing Systems

In Table 2.1 and Table 4.6 we already get some idea on the capabilities of existing systems. These systems can mainly classify the following postures:

1. Proper Sitting
2. Leaning Forward and Backward
3. Leaning Sideways
4. Legs Crossed

For activity tracking, we have existing fitness bands and smartwatches such as the Apple Watch Series 4, Fitbit Flex. For wheelchair monitoring specifically, there are specialized systems such as SmartWheels and FreeWheel. FreeWheel however is currently in the research phase.

2.10 Research Goal

The goal of the research is identified as

> To design and implement a prototype system that senses high frequency postures of and facilitates self activity tracking for wheelchair users, while suggesting a useful intervention strategy

The design decisions made to achieve these goals are:

1. Use of the earable as the additional modality. This is because of the increasing use of wearable computing to monitor ADL, and the push towards wireless earbuds in general as the device of choice for audio.
2. Fusion of IMU data to measure the tilt of the head, in order to identify head and neck posture.
3. Using the IMU to monitor activity.
4. Use FSR data to classify neck and pelvic posture.
5. Implementation of a decision tree to analyze classified posture over time to make the system output "ready for actuation".
6. All processing of the data to be done locally and on off the shelf hardware to immunize the system to connection failures and make it cost effective.

Finally, an evaluation validating these design choices is provided by comparing our system to existing systems in Chapter 4

Chapter 3

System Design

The goal of our system is to enable just-in-time support of wheelchair users regarding their improper sitting posture and postural changes. To this end, the system must meet three key requirements:

- Real time identification of posture and intervention decision.
- On Device processing for low-latency and resilience to possible connection failures.
- Ability to detect neck and pelvic posture along with back posture.
- Ability to track basic physical activity of the user.
- Design an intervention strategy for the user in case of improper posture or insufficient activity.

Existing systems are able to detect postures that have huge distinction between them. These postures are not necessarily of most use to the user due to their infrequency of occurrence. Pelvic postures, neck postures, and intermediate postures like slouching are more relevant in day to day life. Hence a system capable of recognizing those postures is needed.

For activity tracking, popular devices have only just started to supply features for wheelchair users, such as the Apple Watch Series 4 which only launched in 2018. Providing users with similar or more features to monitor themselves with different hardware allows them more freedom to choose a more preferable system than being dependent on a single option.

3.1 Hardware

3.1.1 Force Sensitive Resistor

The placement of the FSR's(Figure 3.3a) on the wheelchair is inspired by [28], where although their design was constrained by the number of analog pins available on Arduino Due, the results obtained by them with such a placement were satisfactory. To that end, our system consists of twelve FSR's, seven of which are placed on the seat of the wheelchair in a hexagonal pattern with and five are placed on the backrest in a square pattern with one in the centre of both(Figure 3.4a). Such a spread of sensors enables us to obtain the pressure distribution of the user over all areas of contact with the wheelchair. The FSR's send data to the Arduino Mega fixed at the back of the wheelchair which in turn forwards it to the Raspberry Pi fixed next to it.

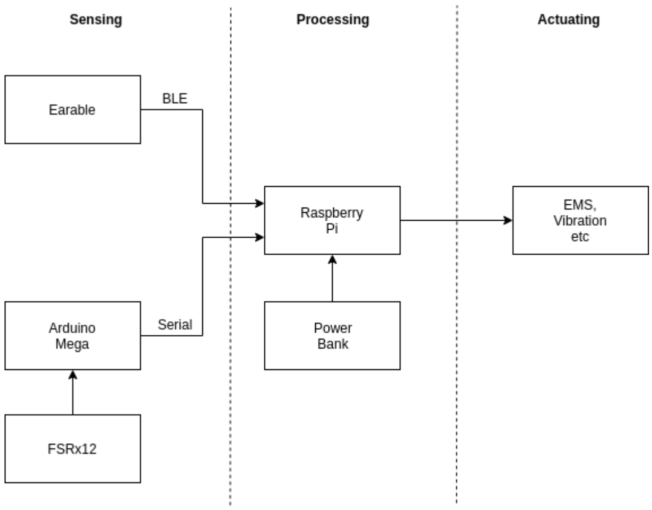


FIGURE 3.1: Communication Diagram

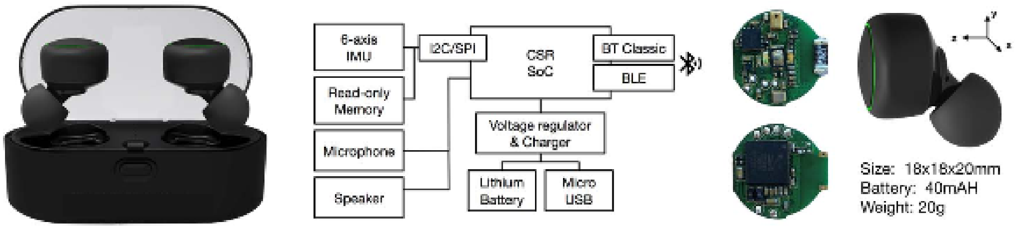


FIGURE 3.2: eSense earable device, schematic, and reference coordinates

3.1.2 Earable

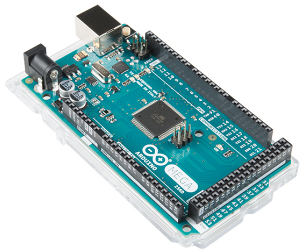
The user is required to wear the eSense earable (Figure 3.2) in order for the system to work. The earable consists on a 6-axis IMU in the left earbud. This earbud allows us to capture the head movement with high accuracy. It uses Bluetooth Low Energy(BLE) to transmit sensory data to the Raspberry Pi. The decision to use the earable as a sensory input is twofold: First, we want the data collection to be as non-intrusive as possible. The earable provides for a novel way of non-intrusive data collection[85] as they serve their original purpose of regular wireless earbuds used as an audio device. Second, the user must be able to put on and remove the sensor comfortably without assistance. Existing systems such as [79] place an Inertial Measurement Unit(IMU) at the back. This is difficult to place properly and remove without assistance for the wheelchair bound. Moreover, while such a position may be suitable for posture prediction in tasks where the body is free to move in all directions, for the wheelchair bound it makes for an unpleasurable sitting experience.

3.1.3 Raspberry Pi

To enable on-device processing a Raspberry Pi Model 3B(Figure 3.3b) is fixed at the back of the wheelchair next to the Arduino. It receives data both from the earable and the FSR's and performs all the computation. The Pi receives power from a power bank, also attached at the back of the wheelchair, via a micro-usb cable.

(A) Force Sensing Resistor

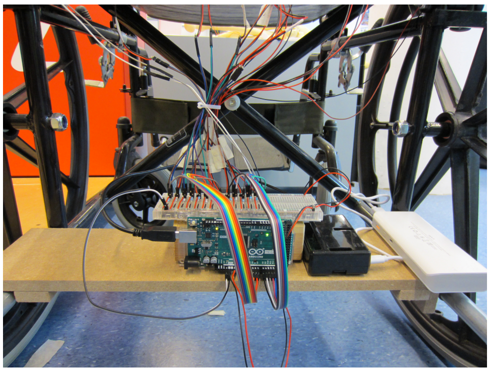
(B) Raspberry Pi Model 3B



(C) Arduino Mega

FIGURE 3.3: Hardware

(A) Front view



(B) Back view

FIGURE 3.4: Wheelchair

3.1.4 Arduino

An Arduino Mega(Figure 3.3c) is fixed at the back of the wheelchair. Twelve analog input pins from it are used to obtain FSR readings via a pull down resistor of 3.3KΩ. The Arduino derives power from and transmits data to the Raspberry Pi via a serial interface connected by a USB cable(Figure 3.4b).

While the system provides opportunity for actuation via ports both on the Raspberry Pi and the Arduino, no such implementation is made on the current prototype.

3.2 System Flow

3.2.1 Data Collection and Alignment

Figure 3.5 depicts a single data packet from the earable. Each field is decribed as follows.

CmdHead	Packet Index	CheckSum	DataSize	Data0	....	Data11
0x55	0~255		12			

FIGURE 3.5: Earable Data Packet

- **Packet Index:** Sequential numbering of subsequent packets. It lies between 0 and 255.
- **Checksum:** It is used to verify the data carried by the packet. It is calculated as

$$CheckSum = DataSize + Data0 + Data1 + ... + Data11(onlyLSB)$$

- **Data0, Data1:** Gyroscope X high byte, Gyroscope X low byte
- **Data2, Data2:** Gyroscope Y high byte, Gyroscope Y low byte
- **Data3, Data5:** Gyroscope Z high byte, Gyroscope Z low byte
- **Data6, Data7:** Accelerometer X high byte, Accelerometer X low byte
- **Data8, Data9:** Accelerometer Y high byte, Accelerometer Y low byte
- **Data10, Data11:** Accelerometer Z high byte, Accelerometer Z low byte

The earable generates data in hexadecimal format. Moreover, the acceleration is denoted as a multiple of G force. Accelerometer data is converted to m/s^2 and gyroscope data is converted to deg/s units. This is done as follows.

$$Acc_i* = \frac{(Acc_i highbyte \times 256 + Acc_i lowbyte)}{8192}$$

$$Gyro_i = \frac{Gyro_i highbyte \times 256 + Gyro_i lowbyte}{65.5}$$

* Acceleration is obtained in G's

where i refers to x, y, z axes.

The Arduino transmits data not in packets but in a stream of bytes with an index number between 0 and 255 heading each stream. The sensors are sampled at 50Hz as in [86]. To ensure reliability of the final output, simultaneous sampling of the sensors is paramount. Relative to the sampling frequency, synchronization between the two devices, accurate to the millisecond is deemed necessary. The earable does not contain a local clock. However, due to the close proximity of the earable to the Raspberry Pi, there is negligible propagation delay as compared to the desired accuracy between the two. The unix time used by the Raspberry Pi suffices as an indicator of the earable's time.

Figure 3.6 shows the difference in time for every packet received from the earable. As seen, the difference in time is not constant at the frequency of transmission, i.e. the packet is received at earbud at seemingly arbitrary times. the first packet is received later than all others as it accounts for the time taken to change the state from no transmitting to transmitting sensor values. The inconsistency afterwards is due to the Connection Interval between the earable and the Raspberry Pi, a feature of the BLE stack. To conserve power, BLE devices do not transmit data as and when it is available, but at regular intervals. The

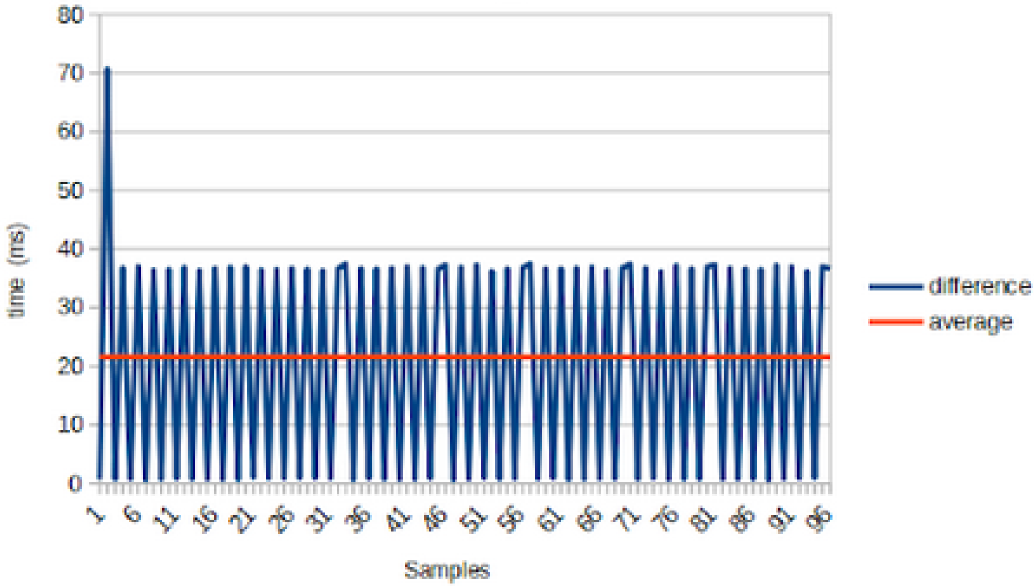


FIGURE 3.6: Difference in subsequent packet received from the earable

central device (Raspberry Pi in this case) may suggest a minimum and maximum connection interval time and in most cases the peripheral (earable in this case) would transmit at intervals within that range. However, this is only a suggestion and the actual connection interval is determined by the peripheral. For our system, the Minimum Connection Interval was set at 20ms and the Maximum Connection Interval was set at 40ms. These are the lowest permissible values. Note that the connection interval is independent of the data sent and the sampling frequency. It is possible for multiple packets to be sent in the same transmission burst. The average interval of all transmission times is 21.45 ms which is roughy the operating frequency. The Arduino transmission time is relatively stable as it is as the data is sent as it is sampled by the Arduino and sent immediately as well as serial connection is more reliable.

A initial pulse is sent to both devices simultaneously to begin transmitting. The earable takes more time than the Arduino to begin transmitting. All data sent by the Arduino until the earable starts transmitting is ignored. This leads to synchronization from the very first packet. Index numbers on both the packets allows us to track any drop of packets and compensate for it by dropping the corresponding packets from the other device. This however has so far not occurred during experimentation.

An experiment was conducted to determine the drift of Arduino's clock as compared to the Unix time. The Arduino was left on for 3 days and its time was regularly monitored. It was discovered that the Arduino clock drifts by 0.001247 ms/s, i.e a drift of 1ms approximately every 802s. To enable continuous use of the system while maintaining accuracy, the Arduino sends every 39999th sample at 19ms instead of the regular 20ms. This introduces inaccuracy for that one sample. However that is inconsequential compared to the high and continuous frequency of the system. On the upside it allows implementation of a very simple synchronization algorithm. This allows it to compensate for drift by itself without any interference from the processor.

3.3 Head Tilt

It was attempted to fuse the FSR readings with the IMU readings to get an estimate of the angle of the of the user's upper body in all dimensions similar to the work done in [79]. However this was unsuccessful for the following reasons:

1. The seat and back rest of the wheelchair are flexible. This leads to the FSR not recording the actual value of the pressure exerted by the user as some of it is absorbed by the seat cushion in attaining a resting state. Zhang et al. [79] do not mention this as a limitation of their design.
2. The FSR's generate force as a function of resistance and operate in three ranges. The first is when a small force is applied, it shows an immediate increase in resistance, also known as actuation force, second, the force and resistance maintain an inverse power law relationship, and finally, when saturation is reached meaning which leads to an increase in force not causing a corresponding increase in resistance. This behaviour is illustrated in Figure 3.7. The saturation may be reached by long continuous operation, or towards the end of the FSR's measurement range. The saturation point may be pushed farther by using sensors with a larger surface area. This makes the system unsuitable for both, (1) Continuous usage during at a stretch, and (2) Regular usage during the life of the product.

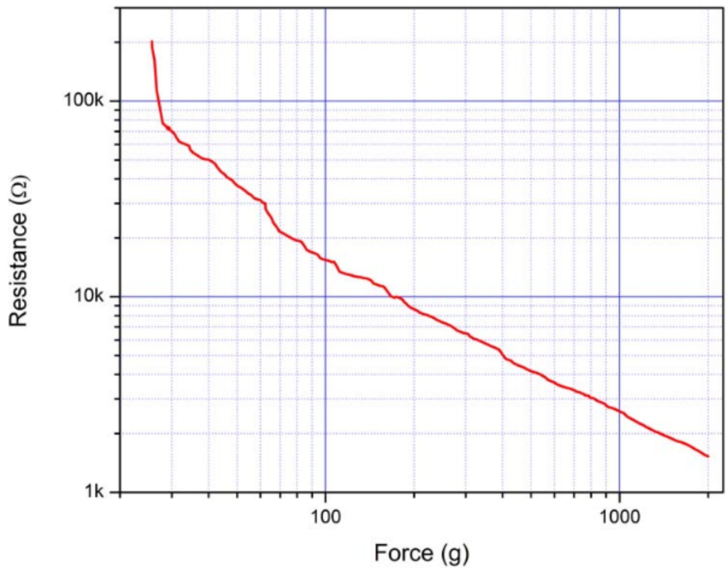


FIGURE 3.7: Force vs. Resistance characteristics for FSR

To overcome this limitation, an Extended Kalman Filter is applied to fuse the earable gyroscope and accelerometer values to get an estimate of the tilt of the head in degrees as explained below.

- Predict

$$\hat{\mathbf{x}}_{k/k-1} = \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1/k-1} \tag{3.1}$$

$$\mathbf{P}_{k/k-1} = \mathbf{F}_{k-1}\mathbf{P}_{k-1}\mathbf{F}_{k-1}^{T} + \mathbf{Q}_{k-1} \tag{3.2}$$

- Update

$$\mathbf{S}_k = \mathbf{H}_k \mathbf{P}_{k/k-1} \mathbf{H}_k^T + R_k \tag{3.3}$$

$$\mathbf{W}_k = \mathbf{P}_{k/k-1} \mathbf{H}_k^T \mathbf{S}_k^{-1} \tag{3.4}$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{k/k-1} + \mathbf{W}_k(\mathbf{z}_k - f(\hat{\mathbf{x}}_{k/k-1})) \tag{3.5}$$

$$\mathbf{P}_{k/k} = (\mathbf{I} - \mathbf{W}_k \mathbf{H}_k)\mathbf{P}_{k/k-1} \tag{3.6}$$

where $\mathbf{P}_k$ is the error covariance matrix, $\mathbf{W}_k$ is the Kalman Filter Gain and $\mathbf{Q}_k$ is the process noise covariance. The $\hat{()}$ signifies estimated values. *k/k-1* signifies the value at time prediction *k-1* and measurement update *k*.

The state vector and the measurement vector for the above EKF equations are as follows:

$$\mathbf{x}(k) = \begin{bmatrix} \theta_k \\ \phi_k \\ \omega_{xk} \\ \omega_{yk} \end{bmatrix}, \quad \mathbf{z}(k) = \begin{bmatrix} a_{xk} \\ a_{yk} \\ g_{xk} \\ g_{yk} \end{bmatrix} \tag{3.7}$$

where ω_i denotes the actual angular velocity, a_i denotes the accelerometer output in the i axis, and g_i denotes the gyroscope output in the i axis in the navigation coordinates. The measurement vector in addition contains white Gaussian noise.

The results obtained from the EKF are compared against the results obtained from a complementary filter, which follows the following implementation:

$$\hat{\theta}[t + \Delta t] = (1 - \alpha)[\theta_{gyro}[t + \Delta t]] + \alpha[\theta_{acc}[t + \Delta t]] \tag{3.8}$$

where $\alpha = 0.02$, has been determined looking at literature and empirical testing.

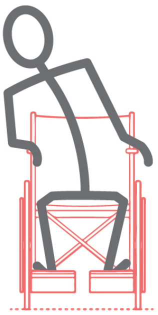
The head tilt finally obtained is used to identify the occurrence of FHP or still head in the user.

3.4 Posture Recognition

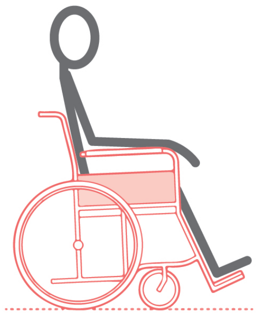
3.4.1 Postures

The system is designed to classify the following postures:

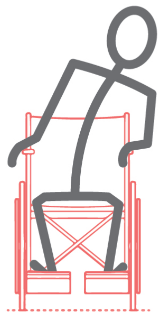
- Sitting Properly(Figure 3.8b)
- Leaning Left(Figure 3.8c)
- Leaning Right(Figure 3.8a)
- Leaning Forward(Figure 3.8d)
- Leaning Backward(Figure 3.8f)



(A) Leaning Right



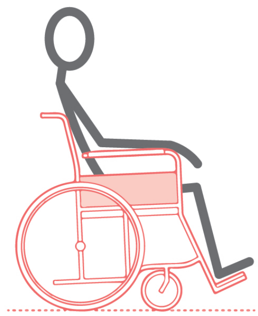
(B) Sitting Properly



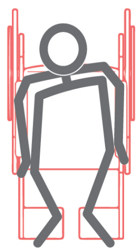
(C) Leaning Left

(D) Leaning Forward

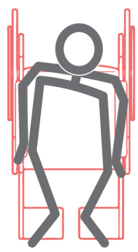
(E) Slouching



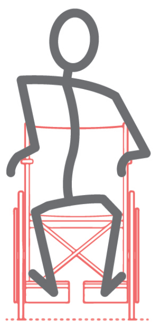
(F) Leaning Backward



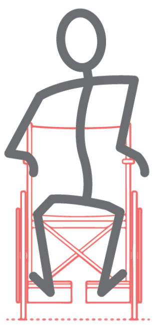
(G) Pelvic Rotation Right



(H) Pelvic Rotation Left



(I) Pelvic Obliquity Left



(J) Pelvic Obliquity Left

FIGURE 3.8: Postures Classified

- Slouching(Figure 3.8e)
- Pelvic Rotation Right(Figure 3.8g)
- Pelvic Rotation Left(Figure 3.8h)
- Pelvic Obliquity Right(Figure 3.8i)
- Pelvic Obliquity Left(Figure 3.8j)

The first four postures were selected as these are postures already identified in literature but not necessarily the most important for a wheelchair user [28]. We add slouching over the capabilities of existing systems. Long duration of continuous sitting leads to inadvertent slouching in most people. Considering that most wheelchair users are confined to a wheelchair for long periods at a stretch, identifying slouching is crucial. Sonnenblum et al. in [7] already warn us about the frequency of pelvic postures. Since most wheelchairs are not customized to the user sitting on them, and that the seats are usually flexible to allow easy transport, users are likely to adjust their pelvic posture to find the most comfortable position. This, combined with wear and tear on the cushion of the wheelchair, pelvic postural deformities are highly likely to occur. It is important to recognize and correct such postures as they cause maximum pressure at the seat surface leading to pressure ulcers [87].

3.4.2 Classification

Samples were collected from five participants for the training data. Each participant was asked to sit in the above mentioned postures for 1 to 1.5 minutes. Since the participants recreated the postures in the presence of the experimenter, the labelling of the data was done as the postures were recreated. Each participant was allowed some time to get comfortable in the wheelchair. The entire process lasted for about 25 minutes per participant.

A K-Nearest Neightbours(KNN) classifier was trained with the obtained data. The choice of algorithm was made after referring to the Table 2.1. It is seen that while more advanced algorithms perform better, the improvement in performance is marginal. This, compounded with the simplicity of KNN implementation makes it an attractive choice. The number of neighbours for the algorithm was decided as 1 from [28] where an increase in the number of neighbours has no impact on the performance.

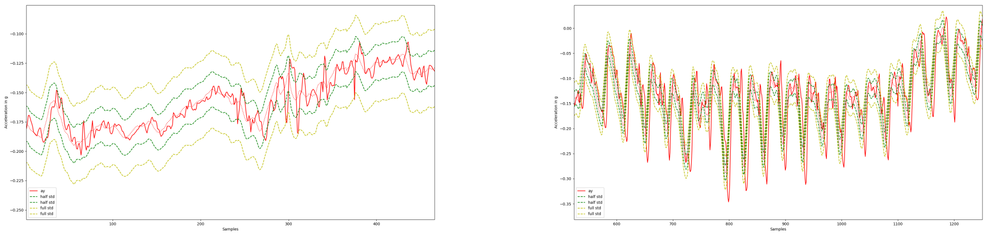
3.5 Activity Tracking

A wheelchair users day can be broadly classified into three activities as realized from [33],

1. No movement
2. Self Propelling
3. Assisted Driving

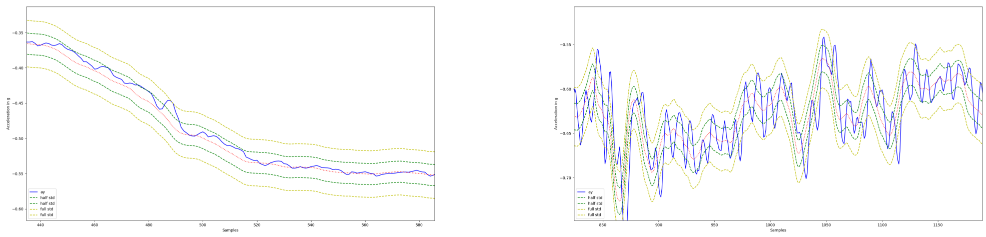
This selection of activities is analogus to counting steps and detecting jogging, running and cycling for able bodied people. While users are likely to indulge in other activities while not moving, those activities, apart from exercises, from a perspective of tracking are not very appealing.

In both Figure 3.9a and Figure 3.10a it is seen that when there is no movement of the wheelchair, the accelerometer y axis data oscillates largely within half standard deviations of the moving average. For assisted driving, it is seen in Figure 3.10b that the data peaks between half and full standard deviations on either side of the moving average. For self propelling, we see in Figure 3.9b that the data goes beyond 1 full standard deviations. We use these peculiarities for each of these activities to classify them in our system.



(A) No Movement (B) Self Propelling

FIGURE 3.9: Zoomed in accelerometer characteristics while Self Propelling



(A) No Movement (B) Assisted Driving

FIGURE 3.10: Zoomed in accelerometer characteristics while Assisted Driving

3.6 Decision

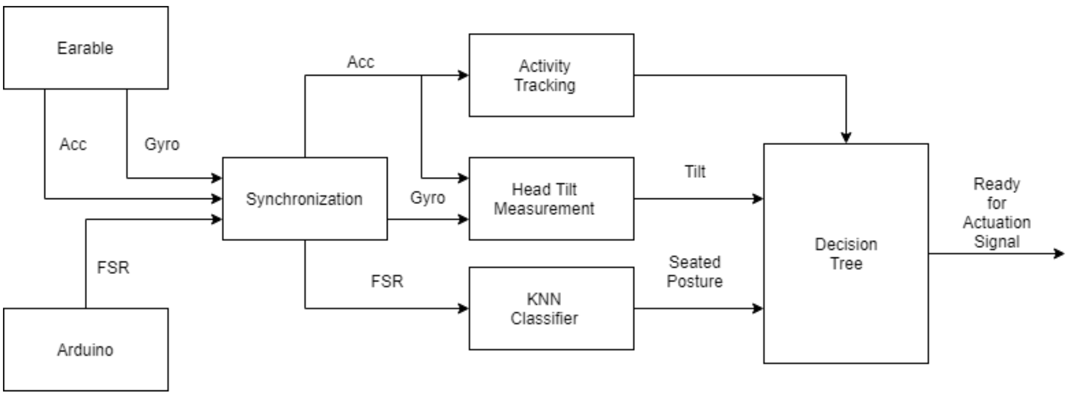


FIGURE 3.11: System Architecture

In Chapter 2 we identified a limitation of existing systems to provide any meaningful intervention to the user. This is largely due to the postures being identified in the moment

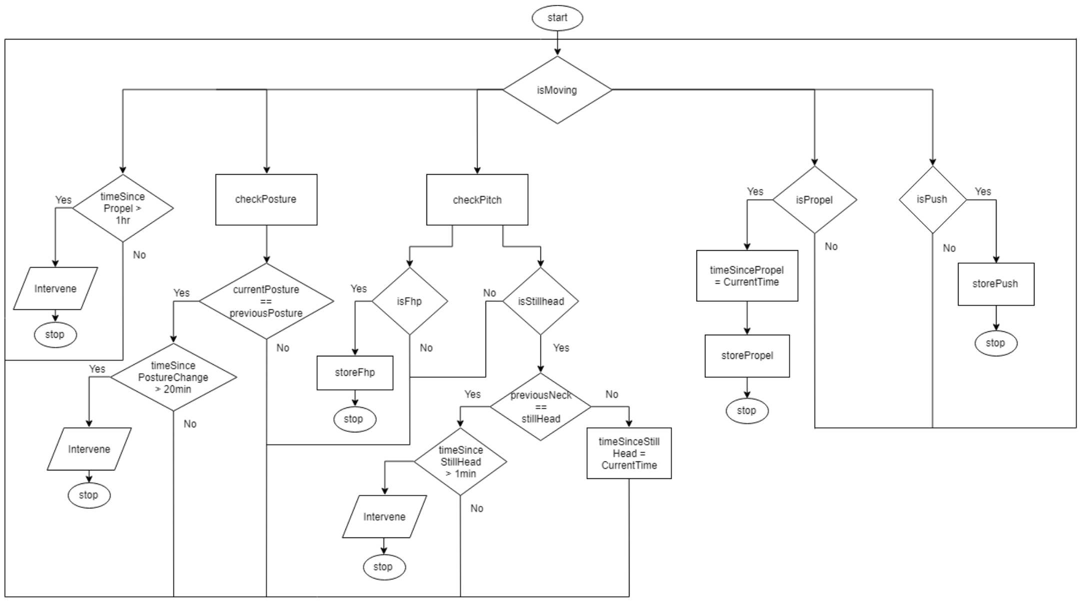


FIGURE 3.12: Decision tree flowchart for Intervention

but no longer tracking or analysis being done on them over time. The output from all three processes: (1) Back and Pelvic posture classification, (2) Head Pitch, and (3) Activity tracking is input to a decision tree as shown in Figure 3.11. The inner workings of the decision tree are given in flowchart form in Figure 3.12. From talking to the staff at a rehabilitation centre, it was discovered that wheelchair bound people must move every 15-20 minutes. Hence in our system, if the user shows no posture change for more that 20 minutes, it is identified.

Furthermore, we have additional functionality in terms on recognizing a still head. It is hypothesized that in cases of an unfortunate incident, the users head would immediately fall down. This will be recognized by the earable. When such a position is maintained for more than one minute and the seated posture is anything but leaning forward, it is identified.

We also have a "Time to Roll" feature which checks if the wheelchair self propelled their wheelchair in the last 60 minutes. If that is not the case then the system records an intervention to indicate some physical activity needs to be performed.

The output from this decision tree is ready for actuation. This step is essential to the system meeting its goal, as it translates the recognition of multiple postures and activity into usable signal for preventative or corrective measures, and is the one that bridges the gap between the performance of a system and the benefit to the user. This is a step that many existing systems ignore. However, possible actuation methods must be studied in order to provide effective intervention. Other features of the system such as activity tracking and FHP are only currently identified and meaningful intervention strategies using such information must be investigated.

Chapter 4

Results and Discussion

In this chapter we evaluate all features of the proposed system using various metrics. In cases where existing systems exist performing similar functions, a comparison of the proposed system with existing systems is provided. There is also a discussion following empirical evaluation where we analyze the benefits and drawbacks of our system as compared to other such systems.

4.1 Performance Metrics

Most features of the proposed system can be broadly put under the umbrella of classification. Hence we provide evaluation on metrics that are standard for all classification systems. These metrics are provided in Table 4.1:

Metric	Formula
$Accuracy$	$\frac{T_p+T_n}{T_p+T_n+F_p+F_n}$
$Recall$	$\frac{T_p}{T_p+F_n}$
$Precision$	$\frac{T_p}{T_p+F_p}$
$F-measure$	$\frac{2.recall.precision}{recall+precision}$

TABLE 4.1: Performance Metrics

where T_p is True Positive, T_n is True Negative, F_p is False Positive and F_n is False Negative

4.2 Classification

4.2.1 Data Collection and Training

The body postures that the system identifies are mentioned in Chapter 3. A data collection campaign was carried out. Six volunteers(three male and three female) having a BMI between 19.7 kg/m^2 and 24.5 kg/m^2 and 20 kg/m^2 and 22.1 kg/m^2(Table 4.2) were given 2 minutes to get comfortable with sitting on the wheelchair. They were then verbally explained the postures that the system classifies. To simulate a real life setting they were then asked to imitate the posture based on their understanding of the verbal description. Based on the users' posture different sensors collect different data.

Sex	Number	BMI Range(kg/m^2)	Remarks
Male	3	19.7 - 24.5	Normal
Female	3	20 - 22.1	Normal

TABLE 4.2: Body Mass Index(BMI) distribution of participants

Posture	***Class***	***No of Samples***
Proper Sitting	1	11957
Slouching	2‘	12243
Leaning Right	3	11654
Leaning Left	4	12196
Pelvic Obliquity Right	5	12196
Pelvic Obliquity Left	6	12183
Pelvic Rotation Right	7	12176
Pelvic Rotation Left	8	12573
Leaning Forward	9	12137
Leaning Backward	10	12160
Total		**121475**

TABLE 4.3: Training data collected for every class

Roughly 2000 samples were collected for each posture from each volunteer. Table 4.3 gives us the total number of samples for each class that was used for training. The data was then divided into a training set and a testing set in a 70-30 split. A K Nearest Neighbours classifier was trained with number of neighbours as 1. The training was carried out offline.

4.2.2 Performance Evaluation

A 5-fold cross validation was implemented to separate a training and a testing set. The performance metrics for the classification are provided in Table 4.5. A high metric is not unusual for such systems as they rely on different contact profiles with the FSRs for classification. This points to the large difference between the different postures and hence clear separation boundaries between them. This feature is exploited by existing systems leading to overall high metrics. However, it must be realized here that high accuracy of the system is not what is targeted here. The focus of the system is to firstly identify more relevant postures. The metrics in Table 4.5, while true for the volunteers who participated in the study, may not be indicative of the real trend due to the limited size of volunteers on which the system was tested. That being said, the proposed system still remains the only system per our knowledge to detect the full suite of seated postures for a wheelchair user. This is also visible in Table 4.6 where a comparison with other systems can be found.

From Table 4.6 we see that all systems identify a common set of postures, namely sitting properly, leaning forward, backward and sideways and all of them claim high accuracy figures. However, for the context of a wheelchair user, identification of these postures have little to no utility in terms of corrective an preventative measures as has been already explained in Chapter 2. This is also where the proposed system outclasses all existing similar systems, as the real difference lies towards the end of the postures list where no other system can identify pelvic postures and only one can identify slouching. It is already identified in Chapter 1 that the needs of a wheelchair user in the context of postures in highly specific and no other system is able to address those needs by identifying the postures that users experience with a higher frequency and in the course of a regular day. These

		Predicted Class									
		1	2	3	4	5	6	7	8	9	10
Actual Class	1	3587	0	0	0	0	0	0	0	0	0
	2	0	3673	0	0	0	0	0	0	0	0
	3	0	0	3496	0	0	0	0	0	0	0
	4	0	0	0	3623	0	0	0	0	0	0
	5	0	0	0	0	3659	0	0	0	0	0
	6	0	0	0	0	0	3655	0	0	0	0
	7	0	0	0	0	0	0	3653	0	0	0
	8	0	0	0	0	0	0	0	3772	0	0
	9	0	0	0	0	0	0	0	0	3641	0
	10	0	0	0	0	0	0	0	0	0	3648

TABLE 4.4: Confusion Matrix

Metric	***Posture Classification***
Accuracy	1
Recall	1
Precision	1
F-measure	1

TABLE 4.5: Performance Metrics for Posture Classification

postures are all the more important given that most existing wheelchair have the kind of flexible cushions that allows the wheelchair to be folded for easy storage and transport. These wheelchairs also encourage the problematic postures identified earlier due to the user. This makes the system easily implementable on most existing wheelchairs, which is not something that is true for many systems in Table 4.6.

The confusion matrix for the classification(Table 4.4) gives us a summary of the classification test on the 30% test set.

	[29]	[40]	[41]	[42]	[43]	[88]	[44]	[30]	[31]	[28]	[89]	[90]	[91]	[92]	[93]	[94]	[95]	Proposed System
Postures																		
Sit Properly	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lean Forward	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓	✓	✓	✓	✓
Lean Backward	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓		✓		✓	✓
Leaning Left	✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓		✓		✓	✓
Leaning Right	✓	✓	✓	✓	✓	✓		✓		✓	✓		✓		✓		✓	✓
Right Leg crossed	✓	✓	✓	✓	✓	✓	✓							✓	✓	✓		
Left Leg crossed	✓	✓	✓	✓	✓	✓	✓							✓	✓	✓		
Sit Forward		✓						✓						✓		✓		
Lean Left Front						✓												
Lean Right Front						✓												
Bent Knees							✓											
Stretched Legs							✓					✓						
Swing													✓					
Shake													✓					
Slouch									✓									✓
Pelvic Obl. Right																		✓
Pelvic Obl. Left																		✓
Pelvic Rot. Right																		✓
Pelvic Rot. Left																		✓
***Accuracy*(%)**	85.9	87.6	82	87	98.9	82.3	NA	97.7	NA	99.48	NA	92.7	94.2	NA	90.9	NA	99.5	100

TABLE 4.6: Comparison of Proposed System with similar existing systems

For all the above reasons, We believe that even if the modality provided by earable and activity tracking and neck posture features are disregarded, the proposed system still provides improvement over similar systems.

4.3 Head Tilt

The earable is used to measure the tilt of the head in the forward direction. The measured tilt is then used for the following functions:

1. Forward Head Posture
2. Still head

The predicted tilt of the head was compared against the ground truth. The ground truth was captured using the web camera of the computer on which the filter was running. A script was written to begin capture simultaneously. The test subject was wearing printable reflective markers roughly along the positions of C7 and C1 vertibrae to enable offline tracking of the joints by the software. The captured video was examined externally on Kinovea(4.1), a widely used sports analysis software to track the movement of the markers in the video. The software generated a 2D coordinates for the markers at all frames in the video. The angle from the position of 3 points using the following formula:

$$Let P_1 = (x_1, y_1), P_2 = (x_2, y_2), and P_3 = (x_3, y_3)$$

$$\mathbf{a} \cdot \mathbf{b} = |\mathbf{a}| \cdot |\mathbf{b}| \cos\theta$$
$$\theta = \arccos\left(\frac{\mathbf{a} \cdot \mathbf{b}}{|\mathbf{a}||\mathbf{b}|}\right)$$

where $\mathbf{a} = (x_1 - x_2, y_1 - y_2)$ and $\mathbf{b} = (x_1 - x_3, y_1 - y_3)$

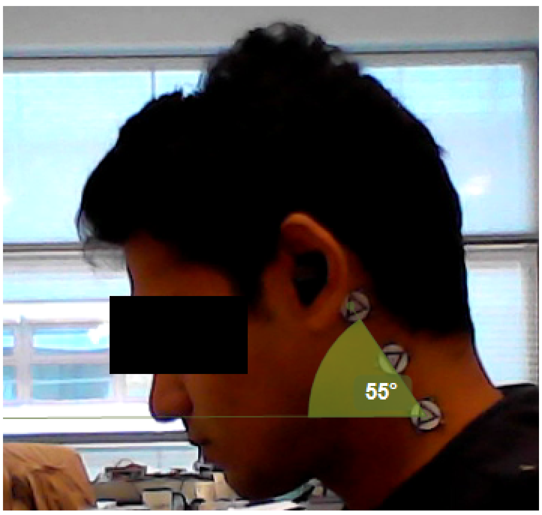
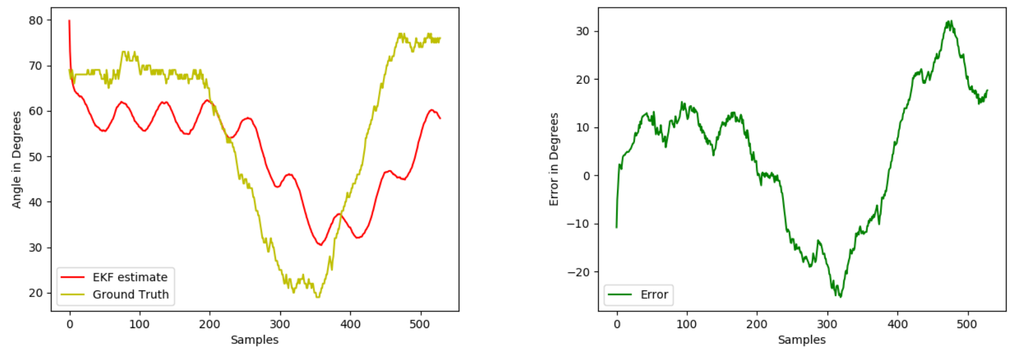


FIGURE 4.1: Angle Tracking on Kinovea

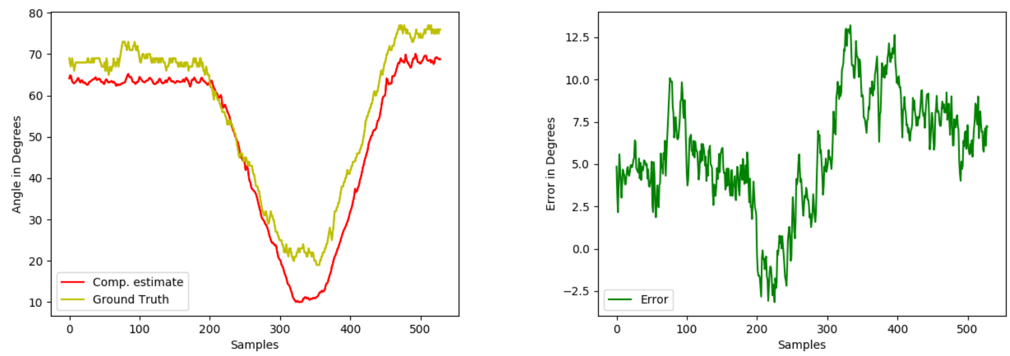
Firstly, two filters were implemented to identify head tilt, the complementary filter(Figure 4.3a) and the Extended Kalman Filter(Figure 4.2a). In Table 4.7 we can also see that the complementary filter is more accurate than the EKF. This can partly be attributed to the difficulty in tuning an EKF. This is a problem is EKF in general as there is no definite methods to tune an EKF. Moreover, EKF uses complex matrix and jacobian calculations. These are much more costly than simple multiplication operations required for a complementary filter. The inaccuracy of both methods can be additionally attributed to the approximation made in measuring the ground truth. In reality, the movement of the neck is a result of the bending of C1-C7 vertibrae and may not be accurately represented by using just C7 as the fulcrum. However, it is difficult to accurately track each vertibrae without specialized equipment. Moreover, two clear observations are made in the case of an EKF:

1. The EKF takes some time to warm up and attain a stable value. The time depends on the initial value.
2. The EKF is slower to react to changes as compared to the complementary filter. This may be due to the EKF dependance on previous states for the next state. At the point where the next state is drastically different from the previous state, the filter may take some time to catch up.



(A) EKF prediction vs Ground Truth (B) EKF error

FIGURE 4.2: EKF prediction and error



(A) Comp prediction vs Ground Truth (B) Complementary Filter error

FIGURE 4.3: Complementary Filter prediction and error

Both these observations are crucial to the system as FHP is identified in the transition from regular head posture to FHP. Since the EKF is slow to adapt to new data, the transition is sometimes lost. This is also unsuitable to record a still head. It is hypothesized that in case of an unfortunate occurrence, the head will instantly fall down and stop moving. The EKF takes greater time to adjust to change in data and hence valuable time maybe

Method	*RMSE*
EKF	14.825
Complementary Filter	6.678

TABLE 4.7: Root Mean Square Errors

lost in identifying the new head position while the EKF stabilizes again. Both of these shortcomings are fulfilled by the complementary filter. For all of these reasons, we use the complementary filter in our system.

4.3.1 Forward Head Posture

We asked six volunteers(three male and three female) to imitate FHP by showing them a diagram of the posture. They were allowed to wear the earable to their individual most comfortable fit and a baseline was recorded for each participant corresponding to their individual regular head posture. The ground truth was again recorded on video. The complementary filter generates the head tilt measurement. A modified smoothed Z-score algorithm([96]) is applied onto these measurements. Figure 4.4 shows readings obtained for one of the above participants. The algorithm is able to identify the positive peak generated during the transition from regular head posture to FHP and the system starts recording the current head posture as FHP, until a negative peak is detected, which signals normal head posture when the system stops recording FHP. The proposed system is able to identify FHP with an accuracy of 99.7%

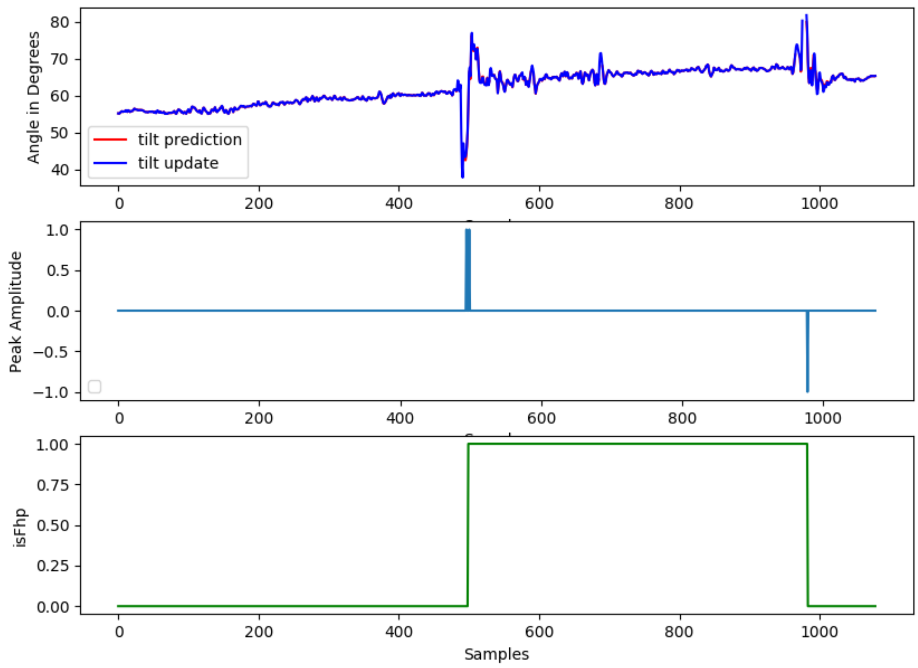


FIGURE 4.4: Forward Head Posture detection

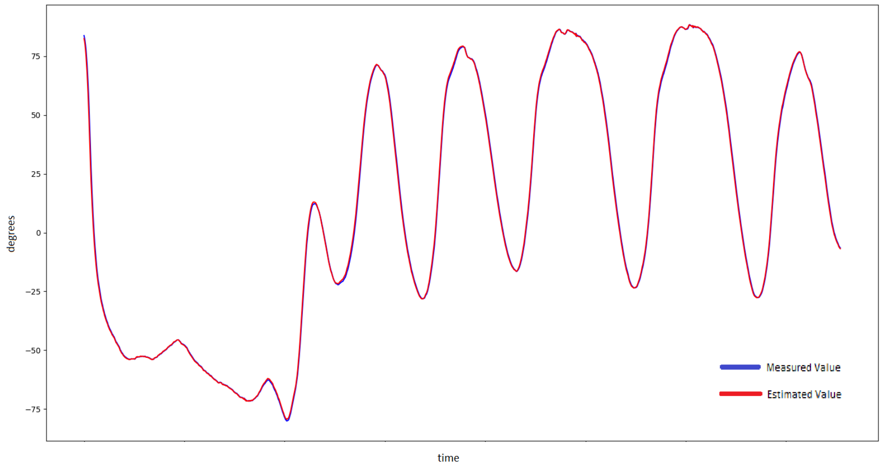


FIGURE 4.5: Head tilt during continuous up-down movement

4.3.2 Still Head

As seen in Figure 4.5, the earable is highly sensitive in measuring the tilt of the head. However, this measurement is only valid is the body posture is not leaning forward, as with the forward movement of the back from the hips, the head will also move accordingly. Hence, if the body posture is anything but leaning forward, and the head tilt is measured as less than 20 degrees for more than one minute, then the current state of the user is identified as having a still head. This is based on the hypothesis that a normal user will not have their head at such a position for such an extended period unless an unfortunate incident may have occurred with them. This feature was tested on five volunteers(three female and two male) and 100% accuracy was obtained.

4.4 Activity Tracking

As mentioned earlier in Chapter 3, we identify mainly three activities,

1. No Movement
2. Self Propel
3. Assisted Driving

Four people were asked to self propel the wheelchair wearing the earable for 2 minutes each. The accelerometer data generated during one of the above exercises is show in Figure 4.7. The part in the figure that is greyed is the period when the actual propelling was carried out. The white parts in the figure indicated no movement. In the lower picture, the an amplitude of 1 indicates detection of self propelling motion, whereas an amplitude of 0 indicates detection of no movement.

Two people were also asked to push the wheelchair both indoors and outside for 2 minutes each. They were instructed to use their own judgement as to at what speed would they push a disabled person at and were asked to vary it depending on the surface. The

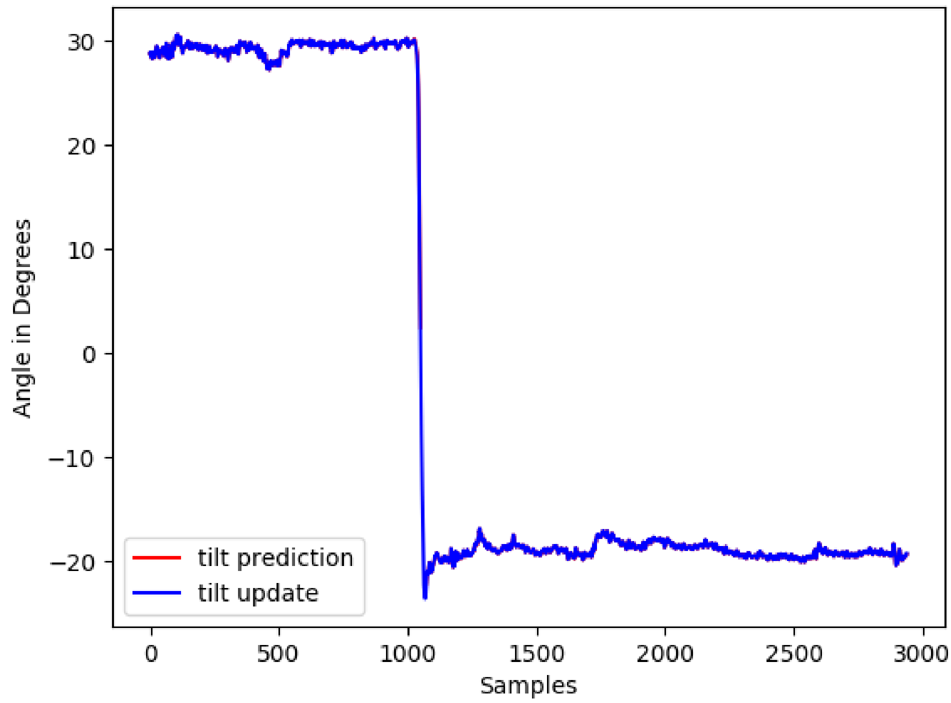


FIGURE 4.6: Change from normal head posture to dropped head

path consisted of turns in both left and right directions with varying degrees. The accelerometer recorded readings as shown in Figure 4.8. Similar to Figure 4.7, the greyed out area indicates occurrence of assisted movement, while the white areas indicate no movement. The small patches of grey in the beginning of the exercise were due to accidental forward-backward movements. Similar to Figure 4.7, an amplitude of 1 in the lower picture indicates the detection of assisted movement, whereas an amplitude of 0 indicates detection of no movement. A portion of the above exercise was also carried outdoors. However, no significant changes were observed in the accelerometer characteristics. This may be attributed to the positioning of the earable on the head, where in case of rough or bumpy surfaces, the body and the wheelchair absorb some of the shock and little effect propagates to the head. The drivers also unconsciously slowed the speed at which they were pushing the wheelchair on rough surfaces.

Performance Metrics obtained for Activity Tracking are provided in Table 4.8. We also compare it to the only similar system we found in out review. The achieved levels of accuracy are comparable to the Apple Watch Series 4 which achieves 90-95% accuracy at high stroke frequencies for self propel[97] when it is set on wheelchair mode. However the watch is unable to identify assisted driving. Compared to [33], the proposed system performs better in identifying self propulsion and Assisted Push, but does not identify sedentary activities.

In Table 4.9 existing systems of different types for wheelchair activity tracking are compared. The Apple Watch Series 4 is able to identify more activities and provide more information, but brings with it the disadvantages of a closed ecosystem, i.e. an Apple watch cannot be used without an iPhone, while the proposed system has all the requisite hardware on-device. This combined with the fact that many old and in need of such a system

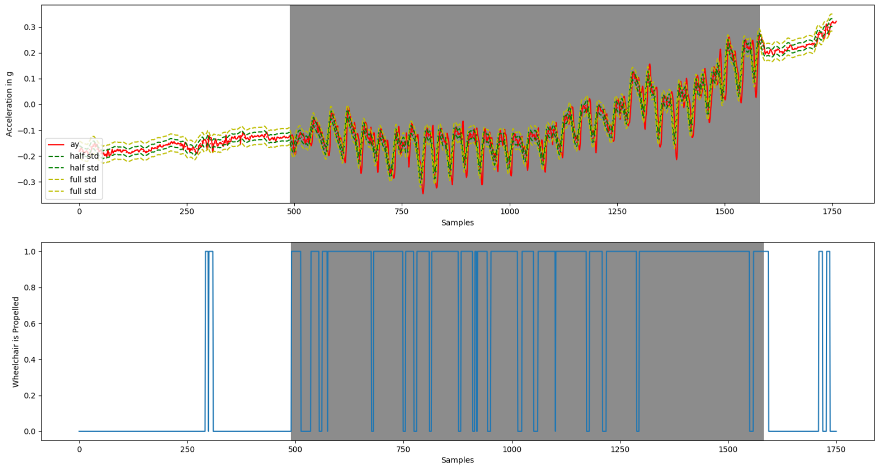


FIGURE 4.7: Accelerometer characteristics and detection of self propel

Metric	***Self Propel***		***Push***	
	Proposed System	[33]	**Proposed System**	[33]
Accuracy	0.911	0.881	0.836	0.746
Recall	0.902	NA	0.843	NA
Precision	0.959	NA	0.909	NA
F-Measure	0.929	NA	0.875	NA

TABLE 4.8: Performance Metrics for Activity Tracking

today do may not use modern smartphones and wearables due to their perceived complex learning curve, it fails to address the need. The Fitbit Flex counts movement in forms of steps. While this is sufficient to measure walking and running movements, for specifically wheelchair users, there are two problems: (1) It measures the manifestation of all wheelchair movements into steps and not the movement itself. This creates room for inaccuracies and the need for a user to assess themselves on unclear information. (2) This has the effect of reminding the user of their (temporary or permanent) inability to walk or run which may have negative psychological effects. Freewheel and SmartWheel require expensive hardware to be separately installed on a wheelchair. While this maybe a better solution in rehabilitation centres, on a personal scale the cost and the entry barrier is way to high. All of these reasons justify activity tracking using earable an exciting area of research.

We see in this chapter briefly two distinct areas where the system contributes to a wheelchair users' well being, namely (1) Posture Recognition nad (2) Activity Tracking. Throughout this thesis we have seen that to provide a complete system to enable wheelchair users to self-monitor themselves, it is essential to have both these features in the system. We also see in the proposed system that different hardware performs different roles for specific features, i.e. FSRs are used for pelvic and back posture only, and earable is used for activity tracking and neck posture. This is consistent with the core principle of multimodality as seen in Chapter 2, which is that each modality should offer complementing information within the system, that the other modalities are unable to provide in order to meet the requirement of Diversity. We believe that the proposed system meets these requirements with a very high degree. Both the modalities individually are highly capable as self

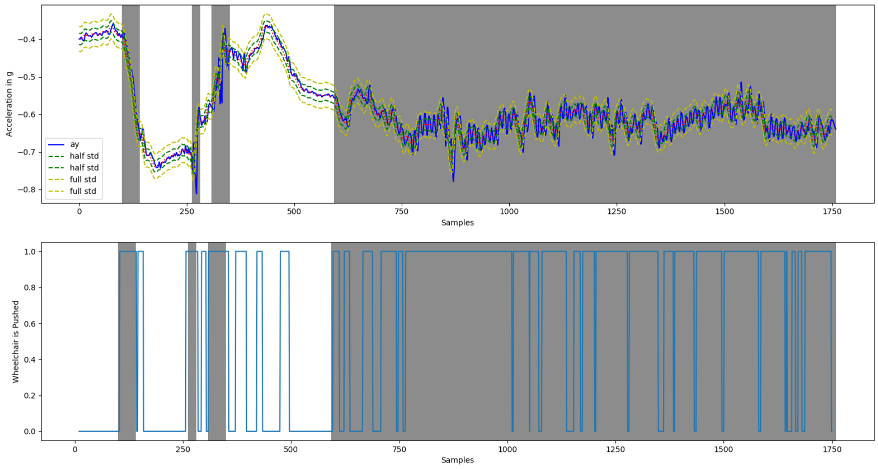


FIGURE 4.8: Accelerometer characteristics and detection of assisted driving

contained systems, i.e the posture sensing with FSRs is one of the best systems of its type, and the earables use as an activity tracker is possible even without the FSRs with the same accuracy, whereas detection of FHP and still head could in principle be used by able bodied individuals as well. But in bringing these modalities together we are able to provide a highly useful solution that meets many needs of a wheelchair user today. In our opinion, this counts as a unique and powerful solution that meets the needs of a wheelchair user today.

A deficiency of this evaluation has been the inability to test some features as they would feature in the real world, such as the "Time to Roll" feature has not been tested for an interval of 60 minutes. This is due to the earable being of a prototype version and was unable to remain switched on for that duration continuously. The features have also been tested on very few volunteers, all of whom were between 22-25 years old. The empirical value of the metrics may change with a different group of users. A broader testing on a diverse group must be done to avoid such uncertainty.

	Apple Watch Series 4	***Fitbit Flex***	***FreeWheel***	***WheelActiv8***	***SmartWheel***	***Proposed System***
Position	Wrist	Wrist	Wrist, wheel and wheelchair frame	Wrist and Wheel	Wheel	Ears
Push	✓		NA	✓	✓	✓
Self Propel	✓	✓*	NA	✓		✓
Energy Expenditure			NA	✓	✓	
Calorie Burn	✓	✓	NA			
"Time to Roll"	✓		NA			✓
Distance	NA	✓	✓	✓	✓	

TABLE 4.9: Comparison of proposed system with existing wheelchair activity trackers

* Counts any movement as steps

4.5 Limitations

The limitations of the proposed system are as follows:

1. The system was not tested with actual wheelchair users. Healthy volunteers were asked to recreate movements experience by wheelchair users. As such, the results may vary slightly with actual wheelchair users, and the system may need to be adjusted accordingly.
2. As explained earlier in 3, the FSR's are not ideal for long term usage. They may develop inaccuracies over time which may affect the final results. For long term usage, the FSR's either need to be changed regularly, or a suitable replacement sensor must be used.
3. The system is designed to measure the head tilt. Tilting of the head is a complex movement involving all C1-C7 vertibrae each tilting with different magnitude to cause a single neck movement. As such, the system assumes a simplified model of the neck tilt where there is a single fulcrum, at C7 vertebra and the neck acts as a rigid body above that fulcrum. The total tilt with respect to the horizontal is then calculated with C1 being the third point in the angle. This may cause some inaccuracies in measuring the actual tilt. This may be solved by placing an additional IMU at the back of the neck.
4. In postures requiring movement from the back or the hip, such as leaning sidewards and leaning forward the system assumes that the entire upper body of the user, excluding the arms acts as one rigid body, i.e. the head of the user moves in synchronization with the torso, exhibiting no individual capacity to move. The system is not immune to head movement in such cases.

Chapter 5

Conclusion

A rising and aging population of wheelchair users justifies the need for self-monitoring technologies for such population. While more advanced and comfortable wheelchairs continue to be developed to better sustain the people using them, a large portion of the population still uses old wheelchairs. These wheelchairs are not only not comfortable but in many cases exacerbate the problems seen amongst patients[7]. It may be highly ambitious to provide access to every person in need to state of the art wheelchairs, however it is indeed possible to provide them with self-monitoring capabilities to track and if needed, change their ways in pursuit of better health.

The general population has largely grown to accept sensory wearable devices for self-monitoring purposes towards better health and fitness within the context of AAL. Existing systems developed for supporting the needs of wheelchair users do so partially and minutely. We believe that wheelchair users are likely to follow the same trend as more devices suited to their needs are available. The proposed system demonstrates, that by exploiting multimodality offered by smart devices, with the earable as a specimen, it is possible to address the needs of this population in a satisfactory and complete manner.

In this thesis, we offer one possible solution to the problems we identify for wheelchair users. We concretely identify the postures that harm them the most in the long term and tailor our solution towards targeting those postures. Succeeding in this, we also maintain the high levels of accuracy that have become the norm in such devices. Moreover, we use the earable detect Forward Head Posture and still head. The principal criteria for multimodality, i.e. diversity is satisfied as both modalities identify complementary but related phenomenon. We also provide an option in what is a very sparse group of devices to monitor activity for wheelchair users. While this may lack in capabilities as compared to some commercially available devices today, the alternative of a device to be worn in the ear paves the way for future research in the direction and must be celebrated.

Such a complete system exclusively for wheelchair users is truly unique and based on our observations is also better than anything else that is currently available. However, the uniqueness does not only lie in the fact that it is the most complete solution, but also that in each of the individual features the system offers, it manages to be either better than or as good as existing alternatives. Namely within posture detection, the standalone wheelchair with FSR's is already better than existing alternatives. Earables can also be used independent of the wheelchair to detect FHP or track activity for all population.

This thesis demonstrates two things, (1) The potential within the earable as a viable option as a wearable device amongst all others and (2) The benefits specific to wheelchair users from sensory devices, of which the numbers are steadily increasing.

Chapter 6

Future Recommendations

The earable has proven to be a highly beneficial addition to the self-monitoring applications for a wheelchair user. Further research must be carried out in order to extract the maximum benefits out of it. Some of these directions may be:

1. Calculating the energy expenditure of a wheelchair user. It is already possible to detect with reasonable accuracy if a wheelchair user is self propelling or being pushed. This can be taken further by correlating it with the energy spent for these activities. Due to lack of similar products under research, a correlation must be developed between the activity and the energy spent using a Portable Metabolic Analyzer. Such correlation may be further narrowed down to different age groups, disabilities, and other activities in the day.

2. A long term tracking of the baseline head tilt during rested postures may be used for early detection of head ptosis or Dropped Head Syndrome(DHS). This syndrome is usually found in people over 60 years of age, and occurs due to weakening of the muscles holding the neck [98]. This is a slowly developing condition and timely intervention may at the least delay its onset.

3. A comprehensive study between the earable and other available wearable devices, such as wrist bands, head bands, belts etc within the context of a wheelchair user must be performed to identify the best individual or combination of devices.

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