Estimation of Ground Contacts from Human Gait by a Wearable Inertial Measurement Unit using machine learning

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Abstract: Robotics system for rehabilitation of movement disorders and motion assistance are gaining increased intention. In this scenario estimation of ground contact is an active area of research in robotics and healthcare. This article addresses the estimation and classification of right and left foot during the healthy human gait based on the IMU sensor data of chest and lower back. For this purpose we have collected an IMU data of 48 subjects by using two smartphones at chest and lower back of the human body and one smart watch at right ankle of the body. To show the robustness of our approach data was collected at six different surfaces (road tiles carpet grass concrete and soil). The recorded data of lower back and chest sensor was segmented into single steps on the basis of right ankle sensor data, then we computed a total of 408 features from time frequency and wavelet domain of each segmented step. For classification task we have trained two machine learning classifiers SVM and RF with 10 fold cross validation method. We performed classification experiments at individual surfaces, hard surfaces, soft surfaces and all surfaces, highest accuracy was achieved at individual surfaces with accuracy index of 98.88%. Furthermore, classification rate at hard soft and all surface are 95.60%, 94.38% and 95.05% respectively. The results shows that estimation of ground contact form normal human walk at different surfaces can be performed with high accuracy using 6D data of angular velocities and accelerations from chest and lower back location of the body.

Keywords: inertial sensor; machine learning; smartphone; ground contact; and wearable.

1. Introduction

Human gait monitoring and gait cycle detection is an active area of research in robotics, eladerly healthcare and bio-metric identification [1], [2], [3]. A cyclic locomotion in a result of natural human walk is known as gait [4]. Every person has a unique gait pattern because of dynamic nature that can be used for authentication and detection purpose [5]. The research on the gait pattern detection is started since 1964 [6] in 1984 Rigas presented a study that discussed foot position on ground manually and gives the different parameters to recognize the gait [7]. For ground contact detection the gait is divided into two main phases swing and stance where in stance phase both feet are on the ground without movement and in swing phase left or right foot are not on the ground. In 1987 Tiberio [8] describe the stance phase in detail and classified it into four regions heal rise, foot-flat, heel strike and toe off. In 1995 Cooper and Adrian [9] present a study that discussed both swing and stance phase and divide the swing phase into leg swing and toe clearance.
In 2001 Hunt et al. [10] presented the vision based motion capturing system with several limitations. In recent years due to advancement in technology and widespread availability of low cost inertial wearable sensors, embedded sensors in smart phones and smart watches that can capture 6D motion data the human gait monitoring is an open area of research. Since last decade a number of studies have been proposed in the field of human gait analysis. A gait base age, gender and height estimation is discussed in [11], [12]. Emotion recognition from human gait is presented in [13], [14]. Human gait recognition [15], [16] foot trajectory estimation from human gait [17] motion reconstruction [18] terrain classification from human gait data, footwear type, age group and soft bio-metrics [19] ground contact detection [20] and stride segmentation [21] are discussed in the literature. Human gait monitoring and estimation of ground contact from human gait by a wearable IMU sensor is an active area of research different techniques have been proposed so far [20], [22]. We propose a novel technique to estimate the ground contact and recognize the right and left step on the basis of gait analysis, Moreover we use six different terrain type data in our estimation process and also gives the comparison of different machine learning techniques used in our methodology.

This study proposed the estimation of ground contact left and right foot classification on different terrain from a human gait by a wearable IMU sensor. Accelerometer and gyroscope sensors data is used for this purpose, Wearable IMU sensors are those that can be fixed or embedded at human body location to measure the orientation and acceleration of the body. For example an ankle mounted IMU sensor measures these quantities at this body location. For data collection two different sensors at different body location are used first is an Embedded IMU (K6D3S3TR) smart watch and second is IMU embedded smart phone (MPU6500) sensor. The purpose of using the set of sensors is to analyze the body motion for validation of proposed methodology performance. Data of 48 persons was collected in total, the age range of the participants is from 17 years to 60 years both sensors were used for data collection purpose. Step segmentation on data signal is performed and then from segmented steps data different time domain wavelet domain and frequency domain features are extracted. A number of supervised and unsupervised machine learning algorithms have been proposed over the years, we apply supervised techniques for estimation and classification purpose and also performed the comparison of the applied algorithms on the basis of accuracy score at different surfaces with two features set. Two machine learning algorithms including RF (Random forest) and SVM (support vector machine) are used for classification task. Experimental results show that estimation of ground contact left and right foot detection at different terrain by angular velocity and acceleration data of segmented steps can be performed with high accuracy. More illustration of the proposed approach and estimation results are discussed in detail in section 3 and 4 of this article respectively.

Related studies

Human gait analysis and estimation of ground contact from human gait is a latest area of research. Human locomotion that is a cyclic combination of movement is called gait [4]. To investigate the normal pattern of the human gait of healthy people in earliest research can be found back in 1964 [6]. In 1970 psychologist validated that human can identify people by their gait pattern. In 1974 body gait pattern were acquired by attaching the moving lights with subjects bodies [23]. Now gait
recognition is categorized into wearable sensors based [24], vision based [25] and floor sensor based. Focus of our study is wearable inertial sensors based estimation of ground contacts, for detail review of methods for gait recognition interested reader are referred to a recent survey paper by Jin et al. [25] and Sprager et al. [16]. A variety of techniques have been proposed since last decade that uses different number of sensors at different location of human body to analyze the gait. Riaz et al. [18] used the accelerometer data of 120 steps normal walk for fully body motion reconstruction. By using the lower trunk sensor data they first identify the ground contact then in second stage combine this information to identify motion reconstruction. Ground contact detection is done on the basis of angular velocity that is positive when right foot accelerated and negative for the left foot, they also presented the limitation of the approach and future work. Kitagawa et al. [26] used foot mounted IMU sensor to estimate the foot trajectory they first estimate the period of flatfoot and use the integration method to estimate the foot trajectory. Kin et al. [20] presented an algorithm that uses IMU data for foot ground contact detection, in their study data of 10 adult participants with five IMU sensor at different location and a video camera that records 60 frame per second is used to record the subject’s motion data.

Sprager et al. [22] estimate the stride segmentation on the basis of local cyclicity estimation of inertial data in their study pitch tracking technique is used that works on the basis of instantaneous fundamental frequencies estimation. Anwary et al. [27], [28] presented a study of automatic gait feature extraction and optimal foot location for sensors placement. For step detection data is passed through high pass filter, zero phase delay filter, low pass filter and then the output of these filters is sent to centroid function and peak detector, hence step detection is done on the basis of peaks. Qaiser et al. [12] presented a study in which they use a single inertial sensor to record one step data and estimated the height, gender and age of the participants by training the RF classifier, for validation a 10 fold cross validation method on 6D acceleration and angular velocity data is used. Zhao et al. [15] presented gait recognition by using image based and wearable inertial sensor time series data with the help of convolution neural network. Hannink et al. [17] provides the comparison of the different techniques from literature at estimation of foot trajectory by using the inertial data of 16 healthy subjects. Subramanian et al. [29] presented the five different methodologies for orientation invariant gait matching and also evaluated these methods on publicly available two large data sets. Ghassemi et al. [30] presented a study on gait sequence segmentation in Parkinson’s disease. For segmentation first of all in data peak detection is done from event based method then dynamic time wrapping (DTW) and Hierarchical Hidden Markov’s Model (hHMMs) is used for gait sequence segmentation. Uniqueness of this study is they use PDTW that is not used before.

In the last two years a lot of work in the field of human gait analysis and ground contact detection has been proposed. Bayat et al. [31] proposed human walking pattern classification by using smartphone accelerometer data. In their work, 20 human subjects data were used that includes 12 male and 8 female after feature extraction of decomposed data the multi-class classifier is used for pattern recognition that give a high accuracy index. Zou et al. [32] done the same work with different data and technique they used unconstrained walking data of 118 subjects and proposed a deep convolution neural network network for better gait feature representation, in their work recognition is done on the basis of deep learning techniques. Semwal et al. [33] presented the
prediction of human gait state they consider the current and previous state to predict the next state through cellular automaton and gives the 16 rules for prediction. Shahabpoor and Pavic [34] estimates the left and right foot ground reaction forces. A quadruped reboot ground contact estimation is done by Camurri et al. [35]. Falbriard et al. [36] estimated the contact time and strike angle of running participants data using IMU sensors. A comparative analysis of footstep recognition is given by Vera et al. [37]. A gait based human user identification by using Accelerometer data is presented in [38] [39] [16]. Carbonaro et al [40] presented a study in which human gait phase detection is done by the mean of smart sensing shoe that has a built in accelerometer sensors that can transmit the sensed data wirelessly to the smart phone, they also gives the comparison of the proposed technique with optical motion capturing system.

3. Materials and method

3.1. Population characteristics

In this study, data of the 48 healthy subjects was recorded in order to achieve the high accuracy index for the training of the classifier that generally gives the better performance on high number of recordings. We collected the data of 48 subjects, 38 male and 10 female subjects participated in the data acquisition process have age range from 17 years to 60 years. The recorded average weight, height and age of the population is 66.4 kg (s = ± 13.0 kg), 170.9 cm (s = ± 7.6 cm) and 28.1 years (s = ± 10.7 years) respectively. Table 1 shows the characteristics of the population. Bar chart of gender and age distribution is presented in figure 1.

Table 1. Summary of population characteristics

| Specification            | Characteristics        |
|--------------------------|------------------------|
| Participants             | 48                     |
| Female to Male Ratio     | 10:30                  |
| Average Height           | 170.9 ± 7.6 (cm)       |
| Average Age              | 28.1 ± 10.7 (years)    |
| Average Weight           | 66.4 ± 13.0 (kg)       |
3.2. Placement and specification of sensor

A high number of built-in sensors are available in modern devices such as in wearable devices (smart watches) and smartphones. In this research work an embedded smart watch (K6DS3TR) and two android smartphones that have embedded motion tracking IMU sensors (MPU-6500) are used [41]. 3D angular velocity and 3D acceleration is provided by gyroscope and accelerometer respectively. By the use of elastic belt the sensors were tightly attached to three body locations lower back, right ankle and chest of the subjects for inertial measurements of these parts of the body. Figure 2 depicted the placement of the sensors.

Figure 2. Placement of sensors at different body parts. The sensors were placed at three different body location.
3.3. Selection of Walking Surface

In order to show the robustness of our approach six real world walking surfaces were selected, three of which are manmade hard surfaces (tile, concrete, asphalt) and remaining three (soil, grass, carpet) are soft terrains. Figure 3 and Table 2 shows the terrain types used in this research work.

![Terrain Classes](image)

Figure 3. Terrain Classes used in experiments. The six terrain types include: tiles, soil, road, grass, concrete and carpet.

| Specification | Characteristics |
|---------------|-----------------|
| Tiles         | Hard            |
| Road          | Hard            |
| Concrete      | Hard            |
| Carpet        | Soft            |
| Grass         | Soft            |
| Soil          | Soft            |
3.4. Procedure for Data Collection

Data for model training in proposed approach is collected in this phase. To record angular velocities and acceleration data from mobile phone an android based application is developed for data collection, and to capture 6D data from smart watch a tizen frame work based application is developed.

During the recording of sensor data from wearable or smart phone devices it is necessary to set the sampling frequency rate that might affect the classification accuracy. In our data collection procedure sampling frequency is set at 75 Hz. However, by increasing sampling frequency rate impact the good quality of data, but it takes time and require more power and processing of data. In the literature [42] for recognition of physical activity some of the sampling frequency rate are reviewed. For data collection while carrying sensors the participants were asked to walk straight in their natural way for 10 meters from starting to end point, and turn around to complete the 40 meters of walk by repeating the same process 4 time (4x10). On the each representative surface the same experiment was performed with shoe on by the participants.
3.5. Data cleaning and signal segmentation

A moving average filter [43], [44] is used for noise reduction in acceleration data. In our approach, before any other processing to smooth out the raw signal [45] and suppressing of noise a moving averaging filter with window size of 9 frame is applied. The general work flow of the system is presented in the Figure 4. Signal decomposition can be take place on the basis of stride [46], [47]. In our approach the raw input signal was segmented into single step based segmentation [12]. A step is the distance between the alternative feet hitting the ground during walking moreover, during walking the movement of raising one foot and setting it down in new spot is a step. The raw signals of chest and lower back sensor were segmented into right and left steps on the basis of right ankle sensor signals. A well-known technique of detecting peaks and valley in input signal for step segmentation from raw signal is used in this work [48], [1], [49].

For segmentation of signals into single steps we used valleys. Right ankle sensor signals are used as reference to segment right and left foot in chest and lower back sensors signals. For the case of right ankle sensor as the sensor is only attached to the right ankle it will generate the high signal acceleration when right foot accelerated and generate minor acceleration when left foot accelerated. On the basis of this behavior of the signal left and right steps are segmented. In the chest and lower back sensors signals valleys are only detected for gravitational axis of acceleration signal (Y-axis) and all the remaining axis of gyroscope and accelerometer are decomposed on the basis of this. In the case of right ankle sensor the gravitational axis was (X-axis) because of the position of the sensor. We cut the signal between two consecutive valleys for single right or single left step segmentation as shown in the figure 5.

![Figure 5](image-url)  
**Figure 5.** Signal decomposition of chest and lower back sensor into single steps right/left by means of finding valleys in input signal
3.6. Feature Extraction and Selection

For better success rate of classifier it is necessary to choose a good set of features. After step segmentation in signal decomposition phase [50], [51], [52] we computed the wavelet, frequency and time domain features of all the steps. The set of extracted features from angular velocities and acceleration are listed in table 3. A set of 408 features is computed in total, for each step. Entropy, mean, energy, minimum, maximum, power, kurtosis, skewness, inter quartile range, standard deviation, index of minimum, mean absolute deviation, jerk and max-min are the time domain features. For frequency domain features extraction (FFT) Fast Fourier Transform [53] was used that includes magnitude, band power of the signal, maximum value of the signal, energy and 9 coefficients of the FFT. The features were computed for all 6D angular velocities and accelerations except the signal magnitude area that was only computed for x-axis of angular velocities and accelerations. To compute the Wavelet features of the signal five coefficients of the wavelet are used, we also computed the envelop and cepstrum of the decomposed signals and computed the entropy, mean, minimum, maximum, index of minimum, index of maximum, kurtosis, power, skewness and standard deviation from these signals of each step.

Table 3. Specification of extracted features for contact detection

| Feature Domain | Number of Features | Dimension |
|----------------|-------------------|-----------|
| Time           | 116               | 6D        |
| Frequency      | 84                | 6D        |
| Wavelet        | 208               | 6D        |

3.7. Features Normalization

In order to improve the performance of classifier some kind of Feature normalization is required [54], [55]. One method is to calculate the standard deviation and mean of each feature value, for normalization subtract the mean value and divide it by standard deviation [56]. In our study standardization on feature set is applied, the feature set has M data entries and N features and MxN matrix of feature set is obtained. For each feature \( f_{ij} \) where \( i \in 1, ..., N \) and \( j \in 1, ..., M \), we find mean \( \bar{f}_i \) and standard deviation \( \sigma_i \) of the distribution.

The standard deviation of the features distribution is computed as:

\[
\sigma_i = \sqrt{\frac{1}{M} \sum_{j=1}^{M} (f_{ij} - \bar{f}_i)^2}
\]  

(1)

The mean of the distribution is computed as
\[ f \hat{i} = \frac{1}{M} \sum_{j=1}^{M} f_{i,j} \]  

To standardize the features the following equation is used

\[ F_{ij} = \frac{f_{ij} - f \hat{i}}{\sigma_i} \]

This gives us the distribution of features with mean of zero and standard deviation of one.

3.8. Features Classification

We classified our features into two set of features all features that includes 408 features and top 113 features that are selected on the basis of feature importance graph. Classifiers are trained and validated on both set of features for each sensor, both set of features gives almost same results with different training time that are discussed in detail in result section. To evaluate the performance of classifier 10 fold cross validation method is used [57], [58]. Ground contact detection from human gait by using inertial data was the goal of the study, for this purpose two machine learning algorithms including SVM support vector machine and RF random forest are used. SVM Support Vector Machine [59] uses the support vectors to classify the data and have the ability to perform the multi-class classification on data set [60]. Random forest RF is a meta estimator used for classification task and work on the basis of decision trees [61], [62]. We used a 10-fold cross validation method for model training and testing purpose. For implementation of machine learning algorithms Scikit-learn v0.19.2 library [63] is used. Both model RF and SVM are trained and validated on two set of features with top 113 and all 408 features sets. Since we have used two different sensors for data collection process so each model is separately trained and validated for each sensor data.

4. Results

Results were computed and discussed by using collected data of each sensor at different surfaces (carpet, concrete, gross, road, tiles and soil) with two classifier and two features sets. Classification task for each body sensor is performed by using RF and SVM classifiers. To show the robustness of our approach six different terrains were chosen furthermore, we categorized these surfaces into hard surfaces (concrete, road and tiles) and soft surfaces (carpet, grass and soil). Results were computed separately for chest and lower back sensor and are presented in terms of chest and lower back sensor respectively in the following two sections.

4.1. Chest sensor classification

In the case of chest sensor classification to test the performance of presented approach results were computed by using the data of sensor that was mounted at chest of the body location. Furthermore, the data was categorized into individual surfaces, hard surfaces and soft surfaces and results were computed for each category.
4.1.1. With RF classifier

With the RF classifier the highest accuracy was achieved at individual surfaces for the chest sensor, more precisely at road surface with top 113 features the accuracy index is 98.88% while with all 408 features the accuracy index is 98.26%. Classification rate at hard surfaces and soft surfaces with chest sensor are 95.60% and 94.09% respectively. Figure 6 shows the confusion matrices of individual surfaces classification with chest sensor by using two sets of features. In general, in the case of RF classifier the classification accuracy is better with top 113 features. Highest accuracy was observed at individual surfaces followed by hard surfaces followed by soft surfaces with chest sensor.

![Confusion Matrices](image)

Figure 6. Confusion matrices with Accuracy in % of estimation of ground contact at each single surface (carpet, concrete, grass, road, soil, tiles) with chest sensor by RF classifier. First row (a) shows the results of RF with Top 113 features and second row (b) presents the results with all 408 features at each surface

4.1.2. With SVM classifier

With the SVM classifier the highest accuracy was achieved at individual surfaces for the chest sensor, best results were found at road surface with all 408 features the accuracy index is 98.39% while with top 113 features the accuracy index is 97.12%. Classification rate at hard surfaces and soft surfaces with chest sensor are 94.40% and 93.12% respectively. Figure 7 shows the confusion matrices of individual surfaces classification with chest sensor by using two sets of features. In general, in the case of SVM classifier the classification accuracy is better with all 408 features. Highest accuracy was observed at individual surfaces followed by hard surfaces followed by soft surfaces with chest sensor.
4.2. Lower back sensor classification

In the case of lower back sensor classification to test the performance of presented approach results were computed by using the data of sensor that was mounted at lower back of the body location. Furthermore, the data was categorized into individual surfaces, hard surfaces and soft surfaces and results were computed for each category.

4.2.1. with RF classifier

In the case of lower back sensor the highest accuracy was achieved at individual surfaces with accuracy index of 97.75%. Accuracy index at hard surfaces and soft surfaces was 95.55% and 94.38% respectively. Figure 8 shows the confusion matrices computed by RF classifier with both sets of features.

Figure 7. Confusion matrices with accuracy in % scale of estimation of ground contact at each single surface (carpet, concrete, grass, road, soil, tiles) with chest sensor by SVM classifier.
4.2. With SVM classifier

With lower back sensor data by using SMV classifier the highest accuracy index 97% was achieved at individual surfaces. Accuracy at hard and soft surfaces was 91.63% and 91.23% respectively. Confusion matrices of the classification are presented in the figure 9. Detailed comparison of results with both classifiers and features sets is presented in the table 4 while bar graph comparison of individual surfaces with chest and lower back sensor is presented the figure 10.

Figure 8. Confusion matrices of estimation of ground contact at each single surface (carpet, concrete, grass, road, soil, tiles) with lower back sensor by RF classifier.

Figure 9. Confusion matrices of estimation of ground contact at each single surface (carpet, concrete, grass, road, soil, tiles) with lower back sensor by SVM classifier.
Table 4. Classification results for each sensor and both classifiers at individual surfaces, hard surfaces and soft surfaces with top 113 and all 408 features.

| Classification category | Sensor       | Accuracy (%) |          |          |          |          |
|-------------------------|--------------|--------------|----------|----------|----------|----------|
|                         |              | All 408 Features | Top 113 Features |        |        |        |
|                         |              | SVM          | RF       | SVM      | RF       |          |
| Road                    | Chest        | 98.39        | 98.26    | 97.12    | 98.88    |          |
|                         | Lower back   | 97.20        | 97.00    | 96.91    | 97.29    |          |
| Soil                    | Chest        | 97.65        | 97.39    | 96.38    | 97.85    |          |
|                         | Lower back   | 96.68        | 97.59    | 96.54    | 97.75    |          |
| Grass                   | Chest        | 97.33        | 97.17    | 95.59    | 97.73    |          |
|                         | Lower back   | 96.54        | 97.50    | 96.45    | 97.26    |          |
| Concrete                | Chest        | 97.35        | 97.73    | 96.82    | 97.83    |          |
|                         | Lower back   | 91.66        | 93.60    | 90.54    | 94.25    |          |
| Carpet                  | Chest        | 96.68        | 97.40    | 96.53    | 97.40    |          |
|                         | Lower back   | 96.42        | 95.81    | 95.78    | 96.56    |          |
| Tile                    | Chest        | 97.10        | 97.10    | 96.96    | 97.29    |          |
|                         | Lower back   | 96.45        | 96.73    | 95.04    | 96.90    |          |
| Hard surfaces           | Chest        | 94.40        | 95.31    | 91.63    | 95.60    |          |
|                         | Lower back   | 94.40        | 95.11    | 92.03    | 95.55    |          |
| Soft surfaces           | Chest        | 93.11        | 93.45    | 92.03    | 94.09    |          |
|                         | Lower back   | 93.12        | 94.37    | 91.023   | 94.38    |          |
5. Discussion

The objective of the study was the Estimation of ground contact from human gait by wearable IMU sensor. To show the robustness of the proposed approach six different terrains (carpet, concrete, grass, road, soil, tiles) were selected for estimation process, further more we categorized these surfaces into hard surfaces soft surfaces and all surfaces. Data was collected separately on each surface by all the participants. To record the normal human gait pattern we have used two different type of IMU sensors at three different body locations. Two smart phones with embedded (MPU-6500) IMU sensors were used at chest and lower back of the body to record the data. One embedded (K6DS3TR) IMU smart watch at right ankle of the body is used. We segmented the input signals from chest and lower back sensors on the basis of right ankle sensor signal into left and right steps. For each segmented steps we have computed a total of 408 features from 6D angular velocities and accelerations that includes time, frequency and wavelet domain features. We also computed the cepstrum and envelop of the signals in frequency domain. We divided our features into two set of features top 113 and all 408 features, top 113 features were selected on the basis of features importance graph. We have trained SVM and RF classifiers with 10 fold cross validation model on the both set of features. We have performed ground contact classification experiments on hard surfaces, soft surfaces, all surfaces and separately at each single surface. We also computed gender based classification results by dividing the population into male and female subjects. Our results shows that estimation of ground contact at different surfaces is possible with high accuracy. Classification rate by using random forest (RF) is higher than support vector
machine (SVM) classifier for all the cases. Experimental results shows that classification rate with chest sensor is higher than the classification rate with lower back sensor at each individual surfaces.

![Classification Rate Graphs](image)

Figure 11. Line chart plot of RF and SVM classifier to show the results comparison of these at different surfaces by lower back and chest sensor.

Highest accuracy was produced 98.88% by RF with chest sensor while SVM produced the classification rate of 98.39% with same surface and same sensor. The classification rate with chest sensor by RF for carpet, concrete, grass, road, soil and tiles are 97.47%, 97.87%, 97.73%, 98.88%, 97.85% and 97.29% respectively. By the experimental results it was observed that RF outperformed SVM in all the cases. RF produced highest accuracy with top 113 features set while SVM produced highest classification rate with all 408 features set in all the cases. To show the performance of each classifier at different surfaces a line chart comparison of these classifiers is presented in figure 11.

6. Limitations

In our research experiments we only computed the results for left and right foot detection different gait phases and gait recognition should also be considered. In our research work population consist of a total of 48 subjects with 38:10 ratio that includes 38 male and 10 female subjects which is not
a balanced population. Future work can be testing of proposed methodology with balanced population. Placement of the sensor with proper setup at chest and lower back sensor is also a limitation of the proposed approach, in future sensor can be used as more natural way for example cell phone in the pocket and watch at the wrist.

7. Future work

We have computed the estimation of ground contact with recorded human data real time gait phase estimation can be a future work. We can extend our research to monitor the abnormal in their gait recovery process and also estimate the risk of fall. Another dimension of future work is we can estimate the gait phases at different walking speed and stair case and can also investigate more sub phases. In our work we used a traditional technique of supervised learning that can be extended to deep learning.

8. Conclusion

Estimation of ground contact from human recorded gait at six different surfaces is the novelty of our research work. Classification of right and left foot was performed on the basis of inertial data of normal human walk. To record the gait pattern (MPU-6500) embedded sensor mobile phone and (K6DS3TR) embedded IMU smart watch were used. Our experimental results shows that estimation of ground contact can be performed with high accuracy by using chest and lower back movements data. We computed a total of 408 features of 6D angular velocities and accelerations from time frequency and wavelet domain. We further divided these features into two sets, top 113 feature were selected on the basis of feature importance graph. We computed the results by using these two set of features top 113 features and all 408 features. For classification of right and left foot RF and SVM classifier were used. Results were computed at hard surfaces soft surfaces all surfaces and separately at each individual surface with both lower back and chest sensors. Results of gender based estimation of ground contact was also computed by dividing the population into male and female subjects. Highest classification accuracy was achieved at individual surfaces. The classification accuracy at Road surface was 98.88% and at soft surfaces was 94.38%. Furthermore, accuracy index at hard surfaces and all surfaces was 95.60% and 95.05% respectively. We also discussed the results comparison of both classifier that shows RF out performs SVM in all cases. Comparison on the basis of features set shows that RF performed better with top 113 features while SVM gives the best results with all 408 features. Our experimental results shows that estimation of ground contact at different surfaces can be performed with high accuracy by using IMU data of selected body location (chest and lower back).

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