ISSN 2229-5518

# Vision Based Gait by using Smart Phone Technology - Incidence of first time Stroke – Post Analysis.

## Introduction

AHA (American Heart Association) reports that 7.2 million Americans have suffered from stroke and about 0.795 million people are confronted by stroke either new or recurrent every year [1]. Developing countries like India, numbers of stroke patients are increasing every year at the incident rate of 119-145/100000 on the basis of recent population studies. The literature shows that stoke is one of the most life threatening disease in the world and is forecasted as the second leading cause of mortality since 2016 to 2030. [2-3] The high risk of stroke among the aged people started due to modern life style, which lead towards the scientific research on gait pattern monitoring. After rehabilitation 50% of stroke patients faced somewhat levels of motor disability and another 50% are halfway reliant in Activities-of-Daily-Living. A comprehensive survey of recent development of gait recognition has been found rarely. To help the patients of hemiplegia for recovery of their motor function, various Motor learning rehabilitation gait techniques have been used. [4] So as to create suitable treatment techniques for stroke patients, it is critical to precisely procure, evaluate and identify their gait abnormalities. At present, developing countries are involved in various researches in means of the most common method of assessing and diagnosing for the betterment of patients with hemiplegia still depends on various questionnaires.

For diagnostic purpose we may require highly sophisticated expensive Gait Laboratory systems to improve the human motion analysis accuracy significantly. We use well developed software and hardware for Motion analysis systems to capture 2D video and converted as 3D images from each frames of video for reconstruction of body segments [5-6]. High end Cameras are involved to mark and place on specific anatomical landmarks of human track movement [7-8] In order to save time, unmarked emerged system provides valuable results [9]. 3D picture analysis is one of the most accuracy in such a human motion analysis system, but time consuming and expensive. However, these laboratories have disadvantages which include expensive equipment, lengthy setup process, limited moving area, and indoor use only. Sometimes patients may feel uncomfortable during the data collection process in clinical conditions due to the technical equipment and controlled environment. Therefore, they cannot demonstrate their own regular walking. In this study we introduce the smart phone gait pattern capturing where ever they need.

As of 2019, there were more than 25 smart phone application available for motion analysis, price ranged from 5$ to 150$. All these applications are very useful for motion video capturing from the smart phone or gadgets built-in accelerometer and gyroscope. Motion capturing facilities are common in latest smart phones like slow-motion, zooming, side-by-side and frame by frame comparison. Apart from that, some applications automatically make calculation of our manual drawn lines and angles on images. Video capturing is measured by Frame per Second (FPS), the ranges for smart phone application starts from 30–60 FPS. Walking is considered as a slower movements and it can be captured with 30FPS adequately, and running as faster motions captured 60 FPS.In the market the first of IPhone® 5S was the best to capture video at 60 FPS. [10]

IPhone® 11 series to allow for 4K video recording at 24fps or 30fps or 60fps respectively. Over all Gait analysis research regarding the use of Smart phone technology and its applications are emerging and majority of researchers focus on it in various ideas [11-13].Clinical population such as stroke, lower extremity amputation and rheumatoid arthritis are evaluated by smart phone technology[14].

Nobody truly instructs us how to walk. It's just when we get some damage or build up any issue that prompts an anomalous walk that we have to correct it. It requires quality and coordination to walk in what is viewed as an ordinary step. While it may resemble a lower body development, walking includes lower leg versatility (Ankle), trunk control, arm movement and balancing. [15]

A gait cycle is characterized as the period between any two progressive redundant walk events. It consists of two major phases, stance phase and swing phase. The first stage starts with initial contact (IC), which denotes the start of the movement to the ground-reaching foot. The position stage closes with foot-off (FO). Swing stage begins with FO and finishes with initial contact, typically, the stance phase establishes around 60% of the entire walk cycle, and the swing phase comprises of 40% [16]

Factors, like, speed would be viewed as the most delicate measure in the aged people and could be a typical and last articulation of the decay that may happen with aging at any event, when there are no clinically significant modifications or emotional grievances corresponding to walk and portability. There are different sorts of unusual gaits which may occur due to wounds, infections and innate issues. These require consideration and amendment by the specialists. There are different models like contorting, waddling and influencing sideways which instead of using the right muscles, strain the body and result is vitality misfortune. A couple of individuals may build up a postural sluggard after some time. This leads them to slow down while strolling and the strides ends up looking exceptionally. [17]

In our study kinematics of leg movements was analyzed during each participants of PG stroke gait. The measurements and identification of changes in lower limb movements are hypothesized during stroke gait in order to improve the biomechanical alterations and understanding the gait pattern, since the static and qualitative methods widely used in the gait analysis field which doesn't provides information of movement analysis especially.

## Materials and Methods

In this study we claimed 16 hemiparetic post-stroke patients (PG - pathological Group) (8 Male and 8 Female) from our earlier study of 164 Patients (91 Male and 73 Female) who had first time stroke in Al-Madinah Al-Munawarah city, the data was collected during the period of 1st January 2014 to 31 December 2014, [18] as the group 1. At the same time, 16 matched healthy volunteers (8 males, 8 females) were enrolled and entitled as the normal controlled group (CG).

According to this study a total 32 subjects were considered and analyzed. we consider 16 individuals affected and assigned in the first group as stroke patients PG pathological group (male is 8 and female is 8) we include with the following criteria; Acute First time stroke has been confirmed by the CT of brain, MRI and echocardiography with unilateral hemiparesis, Ability to stand and walk for at least a minute without using any assistance, Able to Understand the physician command in order to cooperate with the experimental procedures, Not found other diseases known to affect gait like fracture in lower or upper limbs Their mean weight was 74.4 kg (range: 55-84 kg), mean height was 165cm (range: 154cm - 178cm), mean BMI (body mass index) was 27.5 (range: 24.6 - 29.8) and mean age was 67.52 years (range: 20 - 110 years).. And non affected controlled group as the Second group (CG) consist of 8 male and 8 female we exclude with the following criteria; Lower extremity conditions or neurological, Cardiovascular or respiratory problems, mental disorder or insanity, and pregnancy. Their mean weight was 75.7 kg (range: 45-89 kg), mean age was 45.8 years (range: 25-100 years), mean body mass index was 22.1 (range: 18.5.6-24.3) and mean height was 172 cm (range: 156-181 cm) as shown in table 1.

| **Attributes** | **Stroke Patients Group (GP)** | **Controlled Groups (GC)** |
|---|---|---|
| | **Male 8 & Female 8 = Total 16** | **Male 8 & Female 8 = Total 16** |
| **Age in Years** | ***67.52 ± 2.31*** | ***53.0 ± 5.29*** |
| **Weight in Kg** | ***74.4 ± 8.24*** | ***75.7 ± 6.24*** |
| **Height in cm** | ***165 ± 15.7*** | ***172 ± 12.7*** |
| **BMI** | ***27.5 ± 4.5*** | ***22.1 ± 3.5*** |

*Table – 1 – Demographic presentation of Data post stroke patients*

After clinical examination the data collection were started and a static trial was acquired. The CG participants are asked to walk one by one by barefoot at their own capable of gait speed for 60 seconds. The data was collected for the CG subjects on their cycle for the right and the left sides. Also for the HG participants data were collected on their cycle for the affected side and the unaffected sides.



*Experimental Gait Symmetry:*

At the clinical examination, the patients are requested to walk for 60 seconds at the most comfortable status in order to collect enough data, to ensure the effect measurement, and the subjects' data were guaranteed at the measurement interval of walking. Due to adjustment at the beginning of steady walk 2 seconds of frame data have been removing by trimming videos to ensure the data validity. And the room temperature has been monitored at 25$^{o}$C and relative humidity recorded of 65% during the clinical assessment.

The patients walked independently from the emergency parking to the physiotherapy clinic it's almost 60 ft. Patients are under gone qualitative motion analysis with naked eye verification for the gait pattern. The patients were under taken the signed authorization form that "For medical rehabilitation care herewith I give permission to take video or picture for the purpose of my performance of gait". And it maintained confidently at clinical based video captured device with password protected. Also the clinical testing the video has been forwarded to his medical record file till his discharge from the physical therapy department.

There are two types of variable were analyzed, the first one is associated with lower limb gait cycle called spatiotemporal variables. It consists of the all subjects includes step width, length, stride speed, length, cadence, swing phase durations, support and double support. All these variables has be analyzed as like Kirtley et al [19] accordingly. These variables were calculated according to Kirtley et al. [19]. The second type of variables consisted of those obtained from the joint angle curves, such as maximum, minimum and average range of motion (ROM) of the ankle, knee, hip, shoulder (glenohumeral), and elbow joints in the three movement planes (sagittal, frontal and transverse). The last type of variables analyzed consisted of the lower and upper limb continuous angular variables.

*Detection algorithm:* the position of each Heal Stroke and toe off events of walking located as(x, y) of each position with vector size of n each foot, where n is the number of frame sequences. We intended an approach to get Heal Stroke and toe off events of walking with frontal based gait derived subtracting the vertical components of both feet. When we identified the events of Heal Stroke and toe off then single & double supporting time, derivation of step and stride length are determined with variable names.

*Extraction Algorithm*: we focused the lower limb characteristics of human body motion, which is below hip in order to distract from the full body motion we find to formulate a extraction algorithm. Our approach same as like that of Leu et al. [20] but we using the anatomical model to get hips, knees and ankles instead of projecting vertical and horizontal silhouette pixels. This algorithm divides the silhouette into thigh and feet what we have obtained. Then we calculate the center of gravity (COG) once it's segmented. Let top half left corner is the origin, where $Hip_y$ is the y position of the Hip, Hip to Knee is the height of thigh $thigh_h$ $UHCOG_x$ and $LHCOG_x$ are the x position of COG of the upper and lower half of the Hip segment, similarly we do the same with Knee to Ankle foot.

*Smartphone Implementation:* We were implemented the Sagittal and frontal approaches on IOS using OpenCV model native functions. We were using the two ways of allowed processing a dataset: (i) on a real-time video: the Smartphone camera records the subject walking and processes it at the same time. (ii) On a previously recorded video: the Smartphone records the subject walking and stores it in memory, and then the stored video is processed. The pyramidal multi-resolution method has been used and described in [21] to achieve real-time processing. From video captured a single gait cycle was trapped and analyzed, as first step to the moving subject scene is separated from the clip background using PCA segmentation techniques using the SpeedUpTv+ software [22]. This application can run in either IOS based IPhone or Android based any smart phone and video player of this application can be viewed or played high speed or low speed mode. More over the user can do analyze frame by frame, and zoom in or zoom out with HD format pixel in 6 times. This file format can be stored in multiple storage media either in USB transfer or Wi-Fi transfer with highly protected passwords. Physical therapist will shoot the video while treating with patients by phone in 4G/LTE technology and it was captured in 30 to 60 FPS fps using a quad core at 1.4 GHz Smartphone with 2 GB memory and 30 fps using a tablet with a Tegra K1 quad core processor at 2.2 GHz and 4 GB memory. The size of the input image was reduced to 480 × 270 pixels. However, results shown in Section 3 are obtained using full resolution using the dataset.

High frame rate is chosen for gait analysis at the rate of at least 50 FPS. While shooting the patients are asked to walk forward and backward along 15 to 20 ft at a stretch on line marked floor. [19-19]. Both sides of patient's walk have been captured for left and right side view in the sagittal plane and anterior and posterior view in the frontal plane. The video was capture handheld stabilizer uses tiny brushless motors to achieve amazingly smooth motion in even the most treacherously shaky scenarios by physiotherapist. Frontal plane and sagittal plane video captured in certain distance to cover the full view of the patient walk, each walk has been captured 30 seconds in length of each direction. The overview of gait examination procedure's shown in figure 1.

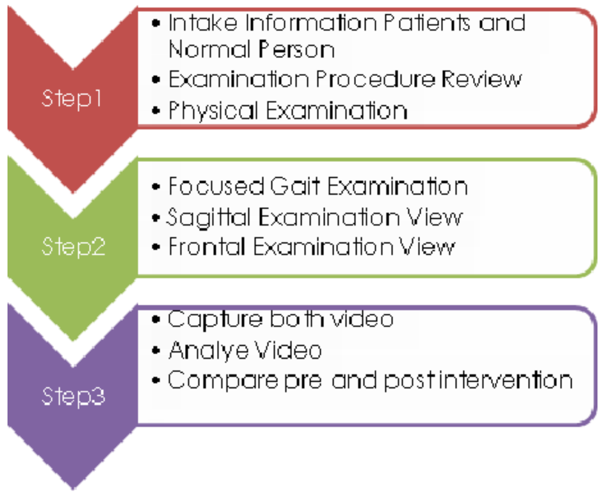


Figure 1 Gait Examination Procedures

*Data Set:* We used the Microsoft Azure Machine Learning (MAML) platform to develop the data set and will be placed in cloud based platform for designing and developing predictive models. The Machine Learning tools access has been provided by the MAML on Web Services. Our main aim to develop K-nearest neighbor (KNN) algorithm with Dynamic Time Warping (DTW) as a distance function accessed through the REST Web Service provided by MAML. To perform a classification between abnormal and normal gait, we use the techniques of bounding box width for sagittal approach, and subtraction between *y* components of each foot for frontal approach and leg-angle time stamp series provided by the extraction algorithm Computed as the angle formed by the hip and each foot.

To avoid over fitting in order to full use of experimental data, the 15-fold cross-validation has been applied to evaluating the picture generalization. The first example is haphazardly divided into 15 equivalent size subsamples. Of the 15 subsamples, a solitary subsample is held as the validated information for testing the model and the rest of the 15-1 subsamples are utilized as preparing information. The cross-approval process is then rehashed 15 times (the folds), with every one of the n subsamples utilized precisely once as the validate information. The n results from the folds would then be able to be found the middle value of (or in any case consolidated) to create a solitary estimation. The benefit of this strategy is that all perceptions are utilized for both preparing and approval, and every perception is utilized for approval precisely once.

## Results

Every person walked to the picture plane towards to fixed smart phone camera, and reverse to walk back once more, rehashing this arrangement multiple times overall. Introduction was finished inside two stages and the body model precision was essentially improved by the first turn. The primary turn empowered precise surface mapping of the blocked side and the changing points of view of the body empowered radii to be all the more precisely decided. Here we are

ISSN 2229-5518

going to describe the performed experiments and obtained results also the recorded dataset for the experiments.

Dataset: According to our proposed approaches, we recorded using sagittal view and using frontal view as a two datasets of subjects in means of walking. All these recording were done in a room with not in the same degree or dimension of walking and avoiding bright light and windows open air to don't get disturbed silhouette at real condition.

We fixed a mobile camera at one end of 20 ft corridor in order to record the frontal dataset and asked subjects to walk towards the mobile camera. We recorded 16 samples of normal subject in controlled group and 16 subjects of Pathological group. We placed a mobile camera at a distance of 10 ft from the perpendicular of the gait direction to obtain a side view. In this case, a total of 16 samples of normal gait and 16 of abnormal gait were recorded. There are 43 for frontal gait and 30 for sagittal gait were captured, there are a total of 320 Heal Stroke events and 319 toe off events for frontal gait and 233 Heal Stroke events and 223 toes off events for sagittal gait. We asked the subjects to walk normally along the corridor and then to walk feigning some of the following abnormalities: a. the subject simulated pain in one of his knees, b. the subject dragged one foot, c. the subject made some small steps with variable speed, and d. the subject depicted random patterns. Each and every angle recorded sample we mark the frame manually by Heal Stroke and toe off events of walking. We also considered the pixel width information of each frames to calculate distances of groups (PG = 1 and CG = 0). A file contains the output of the feet location and feature extraction phases and the positions of heel and toe of each foot, their gradients, and the events of heal stroke and toe off detected. All these output results using full resolution 1920 x 1080 using detection algorithm, which don't corresponds the smart phone using 1/4$^{th}$ of that resolution.

| Normal Gait Dataset | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Method** | Heal Strike | | | | Toe off | | | |
| | Correct | Fault | Skipped | Error | Correct | Fault | Skipped | Error |
| **Sagittal** | 91.2% | 7.8% | 1% | 1.23 f | 92.3% | 5.5% | 2.2% | 1.02 f |
| **Frontal** | 90.5% | 9.3% | 0.2% | 1.78 f | 90.4% | 0% | 9.6% | 1.23 f |
| **Abnormal Gait Dataset** | | | | | | | | |
| **Method** | Heal Strike | | | | Toe off | | | |
| | Correct | Fault | Skipped | Error | Correct | Fault | Skipped | Error |
| **Sagittal** | 90.1% | 2.1% | 6.7% | 1.69 f | 82.6% | 12.8% | 4.6% | 1.58 f |
| **Frontal** | 74.5% | 0% | 22.5% | 2.23 f | 78.1% | 0% | 21.9% | 2.22 f |

Table -2 – The results from detection algorithm of heal stroke and toe off (f-frames)

## Discussion

By using our own datasets for sagittal and frontal gait, we performed experiments and heal stroke and toe off are marked manually in events of each gait sequences of the dataset as ground truth. We assumed Error frame in algorithm and error margin of this manual marking both was set to ± 1 frame. And total global error margin was set to be ± 2 frames. The differences in the proposed algorithm and frames between the walking styles were analyzed, any difference less or equal to the global error margin was considered acceptable. The differences was computed using

$$\textbf{Root mean square error} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$$

Where, n is the number of events of heal stroke and toe off in each case, $x_i$ the frame of event that marked manually as i and $y_i$ the frame of event that the algorithm output as i.

In sagittal approach the results has been given in Table 2 by detection algorithm with filtering methods of heal stroke and toe off. According to the results the corrections are made < 2 frames difference between manual marking and correction algorithm, fault detection are made more than 2 frames of difference between manual marking and correction algorithm also found undetected cases. Moreover, we observed that root mean square error of heal stroke and toe off are lower than our error margin of 2 frames. Unfortunately toe off more clearly marked than the heal stroke. Heal stroke has less cases detected. In Frontal approach the results in table 2 shows that both heal stroke and toe off in normal gait is less than 2 frames of the error margin and grater in abnormal gait. But both results are acceptable irrespective of normal and abnormal gait. We use KNN algorithm to perform the classification between normal and abnormal gait in order to compare the stride length and leg angle of the different gait cycles.

## Conclusion

In our study we focused to find the classification difference between normal and abnormal gait in order to access relative algorithm as per its aspects of control and pathological groups. We considered in testing, foot dragging and joint pain as the pathological abnormal gait as a results suggested to physician for further physical therapy or medication/surgery. In Our future work, we are classifying the pathological abnormal gait due to lack of studies related. Past research has set up that the utilization of video innovation improves stride examination, particularly for less-experienced clinicians. Innovation has progressed to permit in-facility appraisal by joining the utilization of promptly accessible video catch utilizing cell phones. This innovation and its applications can improve conclusion and treatment with negligible expansion of cost or time.

## Study Recommendation:

Further studies in order to improve the heartiness and exactness of the system and extend it to sorts of development designs, other than gait, because of the fact that sports investigation, computer generated reality interfaces, and security systems all offer the need to follow and decipher human conduct and, it is planned to determine gait abnormalities, classify daily activities of users and detect gait phase using artificial intelligence.

## Author Contribution:

**AHA**: Conceived and designed the study, is responsible for the practical part, provided research materials and helped to write the scientific publication analyzed and interpreted data, provided the samples for the research, and helped to write the scientific publication. Results verification and Analyzed Data **BAN**: coordinated the plan of the project and participated in collecting the scientific material. **MSH**: participated in collecting the scientific material and helped to write the mechanism of gait cycle analysis in lower limb prosthetics and orthotics in our discussion. All of the authors have critically reviewed and approved the final draft and are responsible for the content and similarity index of the manuscript.

## Conflict of Interest

The authors have no conflict of interest

## Acknowledgments

The authors would like to thanks the All Medical Rehabilitation College Staff for their guidance, and there is no Fund has been raised for this project.

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