A Pervasive and Sensor-Free Deep Learning System for Parkinsonian Gait Analysis

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Abstract— **Parkinsonian gait is associated with life-threatening consequences such as fall risk in Parkinson patients. Conventional Parkinsonian gait analysis heavily relies on expensive sensors and human labor. In this work, we propose a sensor-free end-to-end system which enables the automated and accurate Parkinsonian gait detection and analysis upon the videos recorded by pervasive cameras. Specifically, we leverage Deep Learning technologies to extract the human skeleton in the video frame and address the camera random angle challenge. By analyzing the gait features, we train a classifier based on a binary decision tree. Out of 16 Parkinsonian gait and 13 healthy gait videos, our system is able to detect the Parkinsonian Gait with 93.75% accuracy and healthy gait with 100% accuracy.**

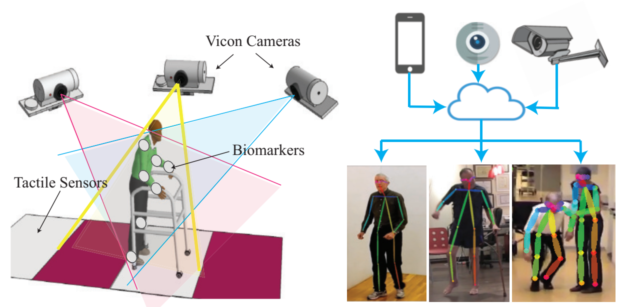
I. INTRODUCTION

Parkinson's Disease (PD) is the 2^{nd} most common neurodegenerative disease in the United States generally affecting people 65 years and older [1]. The severity of the Parkinson's Disease is often associated with major consequences such as higher risk of falling and difficulty sleeping and eating. Allen *et al.* [2] report that a PD patient falls between 4.7 to 67.6 times a year based on the severity of the disease. In fact, the gait of the PD patient (Parkinsonian gait) possesses a strong correlation to the severity of disease [3]. As a result, Parkinsonian gait analysis is part of the standard Unified Parkinson's Disease Rating Scale [4].

Recent advances towards Parkinsonian gait analysis deploy expensive Vicon cameras which requires the individual to walk on tactile sensors and have multiple biomarkers attached to the body (see Fig. 1(a)). The biomarkers enable the Vicon camera to extract the body part positions to analyze the gait. Due to the high cost of Vicon cameras [5], other less expensive gait monitoring approaches have been developed such as attaching accelerometers to the knee joints [6], embedding inertial sensors in shoes [7], or having a nurse constantly monitor the gait of the patient.

Unfortunately, the current clinical approaches have two side-effects. First, the natural gait of the patient tends to change when s/he is aware that sensors are attached to the body [8]. Second, gait monitoring by a nurse is highly subjective, varying from nurse-to-nurse. A non-hindering, pervasive gait monitoring mechanism is required to address the side-effects.

In this work, we propose a sensor-free, automated Deep Learning system which enables the direct Parkinsonian gait analysis on videos obtained through smartphones, surveillance cameras and webcams (see Fig. 1(b)). Specifically, we leverage Deep Learning technologies to automatically and accurately extract the skeleton information from each video frame. To compensate the random capturing angle in real practice, we further develop a projection model based on head pose to map the raw data into a normalized coordinate system. Afterward, we calculate the gait related features to characterize Parkinsonian gait. Our experiment shows that based on the trained classifier, our system can achieves 93.75% accuracy in identifying Parkinsonian gait. The contribution of our work is threefold:



(a) (b)

Fig. 1: Setup Comparison: (a) State-of-the-art Vicon camera deployments using wearable biomarkers. (b) Our sensor-free approach on smartphone/webcam/surveillance camera videos.

- We propose an end-to-end automated system to analyze and classify the Parkinsonian gait on any video captured by pervasive devices such as smartphones, webcams and surveillance cameras.
- We implement the skeleton extraction model to directly detect the joint information from the video frames. Also, we develop a projection model to normalize the arbitrary viewing angles for gait feature calculation.
- We conduct an evaluation on 49 YouTube videos captured by pervasive devices. The result shows that our system can correctly identify PD patients based on their gait features.

In Section II, we provide a related work of current state-of-the-art Parkinsonian Gait analysis and Deep Learning applied to the healthcare domain. In Section III, we describe our Deep Learning Parkinsonian gait analysis system. Sections IV and V evaluates our system and concludes the work, respectively.

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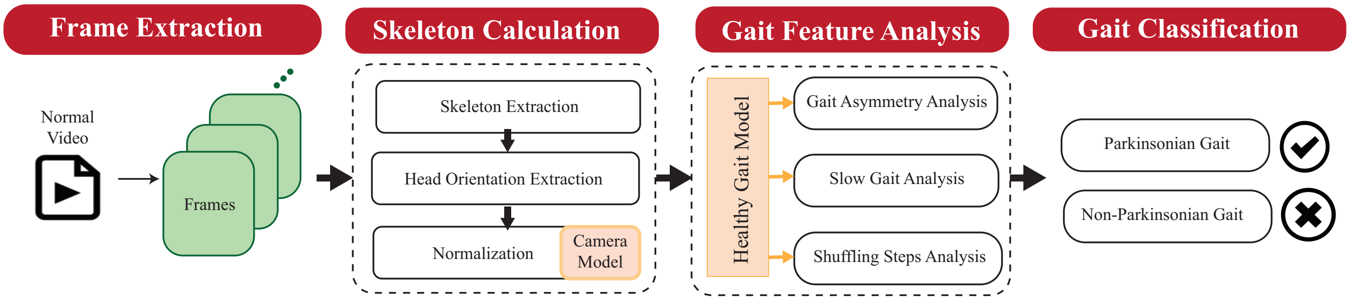


Fig. 2: Our end-to-end system for Parkinsonian Gait Analysis. First, it loads the videos recorded by the pervasive devices. Then, *Knee*, *ankle* and *head poses* are automatically detected from each frame utilizing the advanced Deep Learning technologies. Based on the joints information, it extracts the gait related features. Finally, the classification model is trained to accurately identify the Parkinsonian gait.

II. Related Work

A. Parkinsonian Gait Analysis

Due to the motor deficits caused by the deficiency of dopamine in the basal ganglia, PD patients tend to walk slowly with short shuffling steps and unequal step lengths. Conventional methods use different forms of body attachments to identify Parkinsonian Gait. Salarian *et al.* [9] used multiple gyroscopes on 10 PD patients who underwent deep brain stimulation surgery and validated that their gyroscope model has high correlation with the Unified Parkinson's Disease Rating Scale. Tahir *et al.* [10] employed traditional machine learning to identify a Parkinsonian Gait by having reflective markers attached onto the patients and monitoring them via infrared cameras. The closest wearable-free approach was done by Galna *et al.* [11]. However, their approach requires professional motion capturing hardware.

B. Deep Learning in Healthcare

Deep Learning has increasingly been applied in healthcare informatics. Using Deep Learning to automatically infer a disease based on unusual symptoms is studied in [12]. Deep Learning has also been employed in human pose estimation for activity detection [13]. However, the application of Deep Learning for video-based Parkinson's Disease analysis has only been explored very recently and minimally [14], [15].

III. Methodology

Fig. 2 demonstrates our Deep Learning system to analyze and classify Parkinsonian gait. Our system consists of four modules: 1) *Frame Extraction*, 2) *Skeleton Calculation*, 3) *Gait Feature Analysis*, and 4) *Gait Classification*. Specifically, the system first splits the recorded video into frames; second, extracts the skeleton information from the frames such as knee, ankle and head orientation; third, analyzes the gait features with the extracted information; and finally, classifies a gait as Parkinsonian or non-Parkinsonian.

A. Frame Extraction

The smartphone/webcam/surveillance videos are split into frames using `OpenCV`. Videos of different formats (e.g: avi, mp4, mov, wmv) are processed via the `VideoCapture()` command in `OpenCV` which interacts with the Linux's `fourcc` codecs to generate the frames.

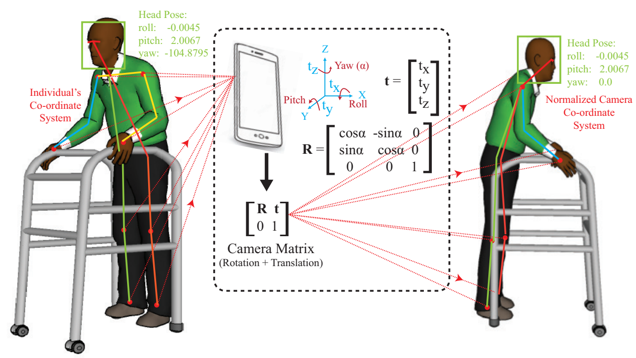


Fig. 3: Process of Normalization: With the head orientation, the view angle of the camera is inferred and the body part positions are remapped onto the camera's frame of reference.

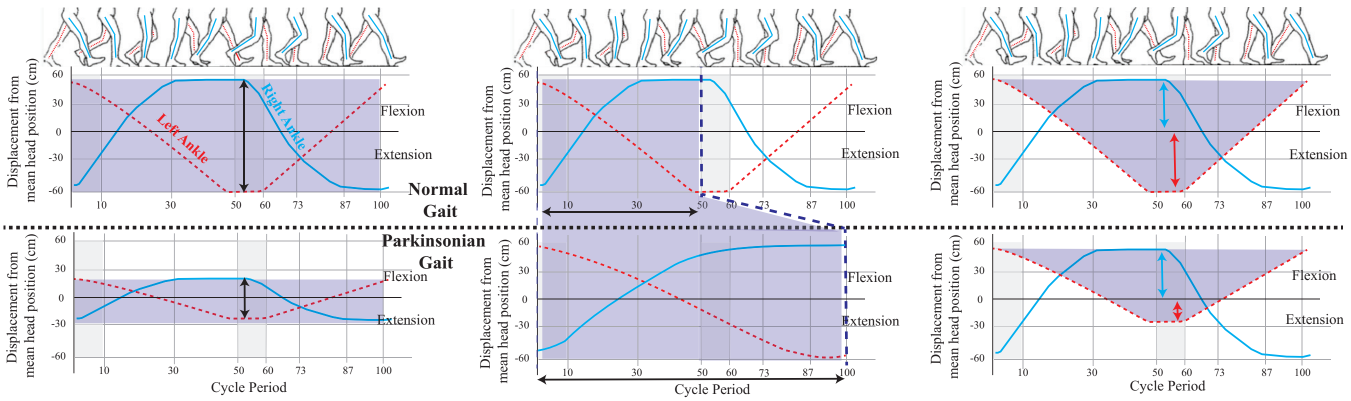
B. Skeleton Calculation

After extracting the frames, the skeleton information such as the position of the ankles, knees, hip and shoulders of the individual is extracted through Deep Learning methodologies [16]. For Parkinsonian gait analysis, we are interested in the positions of the lower body parts - *ankles* and *knees* of both right and left legs. Unfortunately, in normal video recordings, the device might not be placed at a single location for the entire duration of recording and therefore is subjected to continuous changes in viewing angles (e.g: a nurse uses a smartphone to record the gait of a patient from different angles). Situations having moving cameras need to be normalized for meaningful analysis.

The normalization procedure consists of projecting the individual's frame of reference coordinates onto the camera's frame of reference. For this procedure, the viewing angle of the camera needs to be known - which is hard to infer. We, thus, employ a Deep Learning model, Deepgaze [17], to identify the `yaw` of the head with respect to the camera. With the `yaw` information, a camera matrix is automatically populated by our system. The camera matrix $\mathbb{C}$ looks like:

$$\mathbb{C} = \begin{bmatrix} \mathbb{R} & \mathbf{t} \\ 0 & 1 \end{bmatrix},$$

where $\mathbb{R}$ is the rotation matrix which maps the individual's coordinate system to camera's coordinate system. The angle of rotation (α) in $\mathbb{R}$ is the `yaw` value in degrees. $\mathbf{t}$ is the



(a) Shuffling Steps (b) Slow Gait (c) Gait Asymmetry

Fig. 4: Parkinsonian gait feature analysis: *Shuffling Steps* demonstrate minimal displacement of the ankle from mean torso position, *slow gait* is identifiable by long cycle periods, and *gait asymmetry* is identifiable by unequal displacements by the right and the left ankle from the mean torso position.

translation vector that models the linear movement of the camera in the x−, y− and z− axes. A visualization of the normalization procedure is shown in Fig. 3. Using parameters from $\mathbb{C}$, the re-mapping of the skeleton points is done by the equation:

$$v^{camera} = \mathbf{t} + \mathbb{R}v^{individual},$$

where v^{camera} is a vector containing the Euclidean coordinates of the interested body part in the camera's frame of reference and $v^{individual}$ is a vector containing the euclidean coordinates of the interested body part in the individual's frame of reference.

C. Gait Feature Analysis

The *knee* and *ankle* positions for the right and left limbs and the *head* position in every video frame are utilized to analyze the three prominent features of the Parkinsonian Gait, namely, shuffling steps, slow gait and gait asymmetry [9].

Shuffling Steps Analysis: With the *ankle* and *head* positions, the presence of short shuffling steps is detectable. As shown in Fig. 4a, a healthy stride portrays a displacement of $60cm$ away from and towards the torso. On the other hand, the Parkinsonian feature of shuffling steps portray a displacement of $30cm$ from and towards the torso[1]. We model the shuffling steps feature as:

$$f_{step\_shuffle} = ||amp(L_{ankle})| + |amp(R_{ankle})||,$$

where *amp()* is the amplitude of the displacement of right (R_{ankle}) and left (L_{ankle}) ankles in the double support[2] region of a single gait cycle (e.g: between $50 - 60^{th}\%$ along x− axis).

Slow Gait Analysis: The *ankle* and *head* positions are required for analyzing slow gait. We model the slow gait feature as:

$$f_{slow\_gait} = \frac{(\#\ double\ support\ detections)}{avg.\ healthy\ cycle\ period},$$

[1]For all practical purposes, the head aligns with the torso position in the sagittal plane.

[2]double support period is when both the legs are on the ground.

where *avg. healthy cycle period* is $1.2s$ [6]. If f_{slow_gait} approaches 1, then the gait is deemed healthy. If f_{slow_gait} assumes high values (> 5), then the gait is deemed as slow Parkinsonian gait. The high value of f_{slow_gait} is very unique for the Parkinsonian gait since the individual exhibits shuffling steps (by keeping his/her foot close to the ground) as well as exhibits slow gait at the same time.

Gait Asymmetry Analysis: Due to the Freezing-of-Gait syndrome[9] in Parkinson's disease, the right and the left limbs do not move equally away from and towards the torso. Fig. 4(c) demonstrates the stride of a patient experiencing Freezing-of-Gait in the left limb. The presence of unequal amplitudes between the right and left ankle position during double support observed over multiple frames indicates the presence of asymmetric gait. We model the gait asymmetry feature as:

$$f_{step\_asym} = ||amp(L_{ankle})| - |amp(R_{ankle})||,$$

where $amp()$ is the amplitude of the displacements of the right and left ankles from the mean torso position.

D. Gait Classification

The classifier, based on the results of the feature analysis module, consists of training a binary decision tree. The classifier is further employed to automatically detect and classify Parkinsonian gait in the videos.

IV. RESULTS

A. Data Preparation

Cameras	Res.(ppi)	Frame Rate (fps)	Count
Smartphone Camera	1280x720	30	19
Surveillance Camera	352x240	15	14
Webcams	640x480	30	16
Vicon Cameras	2048x1088	250	-

TABLE I: Characteristics of the videos we collected.

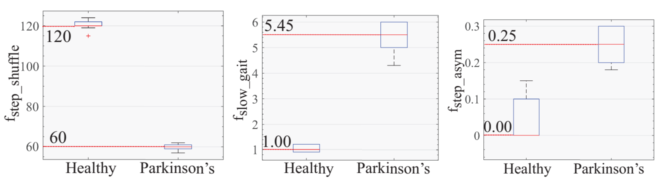
49 gait videos were collected by a Youtube download script[3]. The characteristics of the collected videos are shown in Table I. We can observe that the pervasive cameras provide

[3]https://rg3.github.io/youtube-dl/

a much lower resolution and frame rate than the professional one. The videos were manually validated and labeled into 26 Parkinsonian gait and 23 healthy gait videos by a certified clinician. Specifically, 20 (10 PD + 10 healthy) videos were used as the training set and the remaining 29 (16 PD + 13 healthy) videos were used as the test set.

B. Analysis Results

Fig. 5 shows the analysis of $f_{step\_shuffle}$, f_{slow_gait}, and f_{step_asym} done on the training set (20 videos). As shown in the boxplots, the healthy and Parkinsonian gait observations are distinguishable on all the three features. More specifically, the mean of $f_{step\_shuffle}$ is 60 for Parkinsonian gait while 120 for healthy gait; mean of f_{slow_gait} is 5.45 for Parkinsonian gait while 1.00 for healthy gait; and mean of f_{step_asym} is 0.25 for Parkinsonian gait while 0.0 for healthy gait.



(a) (b) (c)

Fig. 5: Analysis of the gait features: (5a) *shuffling steps*, (5b) *slow gait*, and (5c) *gait asymmetry*.

C. Classification Results

The decision tree in the gait classification module learns the mean thresholds for the healthy and Parkinsonian gait for the three features from the above results (Fig. 5). The test set (29 videos) are then sent through the decision tree classifier which classifies the videos as Parkinsonian or non-Parkinsonian. Our system had an accuracy of 93.75% in detecting Parkinsonian gait and 100% accuracy in detecting healthy gait. One Parkinsonian gait is not identified because the patient is too far away in the video, which affects the accuracy of skeleton extraction.

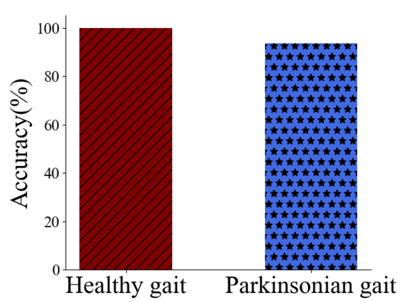


Fig. 6: Accuracy of classification: All healthy gait videos were classified correctly. Accuracy of Parkinsonian giat detection is 93.75%.

V. CONCLUSION

In this work, we propose a Deep Learning system that analyzes and classifies Parkinsonian gaits. We process videos recorded by pervasive devices like smartphones, webcams and surveillance cameras. Our workflow consists of extracting the body part positions, infer the gait features and classify the gait as Parkinsonian or non-Parkinsonian. The impact of our system is that it can save thousands of dollars used in buying Vicon cameras and also enable pervasive gait monitoring in natural environments. In the future, we plan on extending our system to be more robust by analyzing additional features of Parkinsonian gait such as bradykinesia, spasticity and tremors.

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