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Parkinson Hand-Tremor Recognition Using CNN+LSTM : A Brief Review

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Abstract- *Parkinson's disease is a nervous system-related movement disorder. A scarcely apparent tremor in only one hand could be the first sign. Tremors are common, however they're frequently accompanied by stiffness or decreased mobility. The symptoms and indicators of Parkinson's disease vary from person to person. Early warning signs may be imperceptible and go unnoticed. Even when symptoms begin to affect both sides of your body, they usually begin on one side and progress to the other. Tremor, Slowed Movement, Rigid Muscles, Impaired Posture and Balance, Loss of Automatic Movement, Speech Changes, Writing Changes, and others are some of the signs and symptoms of Parkinson's disease. There are currently no particular tests available to diagnose Parkinson's disease. Parkinson's disease is diagnosed by a trained specialist in the field of nervous system conditions based on the patient's medical history, signs and symptoms, and a neurological and physical examination. For non-invasive monitoring, analysis, and diagnosis of individuals with motor disorders like Parkinson's disease, tremor estimation from video is crucial. Since the COVID-19 event, remote and objective assessment of Parkinson's disease motor symptoms has gotten a lot of attention. Many ways for diagnosing Parkinson's disease are discussed in this publication, as well as the technology, tools, and picture datasets used in the study.*

Introduction

Parkinson disease, commonly known as Tremor, is caused by a decrease in dopamine levels in the brain, which affects a person's motor functions, or physical functioning. With the passage of time, the neurons in a person's body begin to die and become irreplaceable. The effects of neurological problems and the decrease in dopamine levels in the body in patients show gradually, making it difficult to detect until the patient's condition requires medical treatment. However, the symptoms and severity levels vary from person to person. Voice loss, loss of balance, and unstable posture are some of the symptoms.

According to the World Health Organization, 10 million people worldwide are diagnosed with Parkinson's disease each year. The risk of developing Parkinson's disease rises with age; today, 4% of Parkinson's disease sufferers worldwide are under the age of 50. Parkinson's disease affects 7 to 10 million people globally every year, according to estimates.[1]

Existing approaches to tremor analysis necessitate the use of specialised sensors, which makes them difficult to implement in practise. Furthermore, the more high-level tremor diagnosis problem or tremor/no-tremor classification is the targeted application of these methodologies.[2] Computer vision assessments of gait[3] and wearable data analyses[4] have already showed potential in detecting Parkinson's disease during motor tasks. However, there are still a number of issues to be resolved[5].

The main objective is to recognize the human hand tremors from videos obtained with standard consumer RGB cameras. The problem is critical in medical applications for assisting medical workers in the monitoring and diagnosis of patients with motor disorders. Traditionally, clinical practise has relied on body-worn accelerometers, which provide accurate measurements but are obtrusive, time consuming to set up, and only allow for the monitoring of a single location per accelerometer. When accelerometers are replaced with a standard RGB camera, a nonintrusive means of measuring full-body tremors emerges, providing a significant advantage in clinical practise.

Literature Survey

Silvia L. Pintea et al, in their paper "Hand-tremor frequency estimation in videos"[2], propose two different approaches for measuring human hand-tremor frequencies: (a) Lagrangian handtremor frequency estimation, which assesses the hand-tremor frequency using the trajectory of the hand motion in the image plane throughout the video; and (b) Eulerian hand-tremor frequency estimation. In Lagrangian method, they first apply the Kalman-filter tracker to the initialised hand locations detected by the pose estimation algorithm. Through this they obtain corrected locations of hand trajectory on which a windowed fourier transform function is applied which provides the PSD (Power Spectrum Density) Function. The maximum frequency is used as the estimated hand tremor frequency. Figure 2.1 shows how hand location changes with tremor and how lagrangian method is used to estimate tremor frequency.

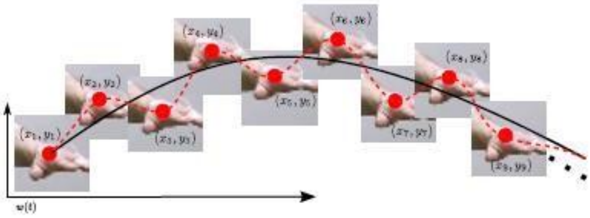

Figure 2.1 – Lagrangian hand-tremor frequency estimation[2]

In Euclerian method, the first step is same as the Lagrangian method. After that they extract local information encoded as phase over different scales and orientations. The frequency of hand tremor is computed using the most informative phasae-image. Figure 2.2 shows how phase images are used to estimate tremor frequency.

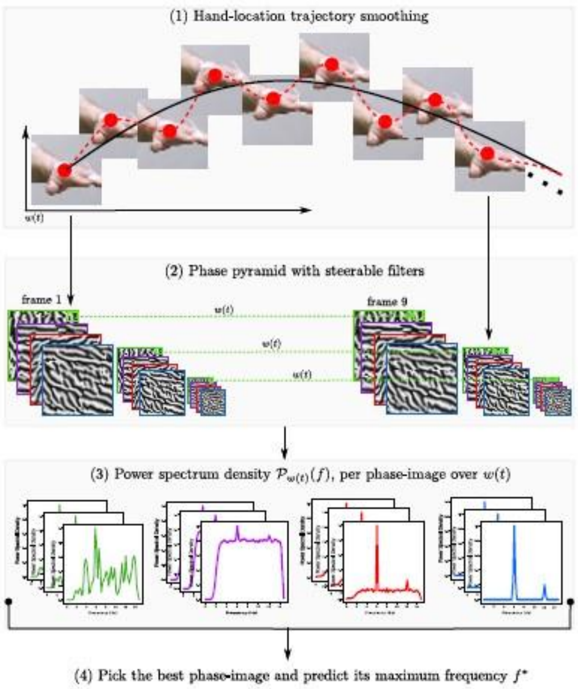

Figure 2.2 – Euclerian hand-tremor estimation[2]

On their planned TIM-Tremor dataset, which contains 55 patient recordings doing a variety of tasks, they tested two variants of each technique. They discovered that Eulerian procedures are more accurate on average than Lagrangian methods, with the difference being significant on jobs with a limited amount of major hand motion but a small hand-tremor motion.

Luay Fraiwan et al, in "Parkinson's disease hand tremor detection system for mobile application"[6], the proposed work created a full system that uses a mobile phone accelerometer to identify and record hand tremor in Parkinson's disease patients with excellent accuracy. The data from accelerometer was pre-processed and the three-dimensional acceleration was calculated as the mean of the accelerations in x, y and z directions. The classification consisted of three steps. First, the data was analysed using wave packet decomposition. In second step, selected parameters were extracted which were used to represent the data. The final step was classification. For classification many classifiers were tested, but at the end ANN classifier was selected for classification. In comparison to previous approaches that involve hardware such as EMG or separate accelerometers, the suggested system may be used on a mobile phone without the need for any hardware setup; the system can also be used in any location without the need to transport the patient to a hospital or clinic. It can also provide remote recording and monitoring systems for Parkinson's disease patients, which helps to improve the quality of treatment delivered to the patients.

Luis F. Gomez et al, in the study "Improving Parkinson Detection Using Dynamic Features from Evoked Expressions in Video"[8], looked into the effectiveness of evoked facial gestures in detecting Parkinson's disease. The author presented that how static and dynamic data can be used to represent hypomimia in Parkinson's disease patients. Face footage of persons eliciting four various facial gestures (Happy, Angry, Surprise, and Wink) were used in this study. The Author has presented a new set of 17 criteria to characterise the expressiveness of evoked facial motions in video sequences. For the Static features approach, a pre-trained ResNet50 with 50 layers and 25.6M parameters was employed. This model is used to generate initial face and used as feature extractor by removing the final decision layer. For each face the model generated a total of 1x2048 feature vector. The dynamic feature approach is structured into 2 blocks: 1) Facial Landmark Detection Algorithm and 2) Dynamic feature Extraction. Mediapipe Library is used initialize 468 face landmarks. A Facial Mesh is generated from these landmark points. Analysing the Facial Mesh, Dynamic features are extracted which are then fed to a SVM Classifier. Figure 2.3 represents the block diagram of PD detection system based on both static and dynamic features. The following diagram shows all the steps and processes included in extracting static and dynamic features of face.

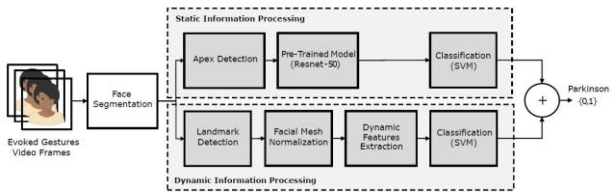

Figure 2.3 - Block diagram of the PD detection system based on static and dynamic features from evoked face gestures[8]

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Yunyue Wei et al, in "Interactive Video Acquisition and Learning System for Motor Assessment of Parkinson's Disease"[9], proposed PD-GUIDER, an interactive video acquisition and learning system for motor evaluations of Parkinson's disease patients. To guide, record, and evaluate movement videos of clinical motor tests, the authors integrated cutting-edge computer vision and machine learning techniques into the smartphone app. The video quality and clinical usefulness of recordings were ensured via an AI-based calibration and interactive procedure. PDGUIDER's promise as an effective AI-based telemedicine treatment for Parkinson's disease was established in a preliminary experiment. With this technology, largescale collection of high-quality and diagnostic-level movies becomes possible. Figure 2.4 shows how the keypoints of body and hand are extracted using PoseNet and HandPose respectively. And using this keypoints, prediction of Parkinson symptoms are made.

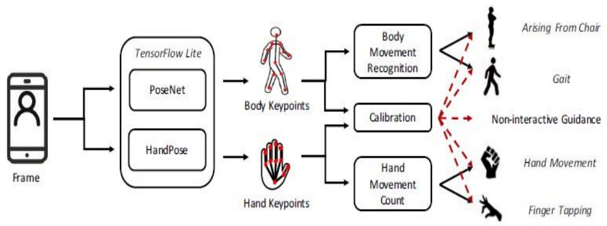

Figure 2.4 – Keypoint estimation and movement recognition in PDGUIDER[9]

Mohammad Rafayet Ali et al, in the paper "Spatio-Temporal Attention and Magnification for Classification of Parkinson's Disease from Videos Collected on the Internet"[10], suggests and tests a new framework for detecting Parkinson's disease using online video recordings. In the proposed system, first the images are extracted from videos and segmented to extract temporal and spatial data using a CNN. After segmentation, feature representations are computed using Fast Fourier Transform (FFT). To understand the potential value of different representations, we implemented and compared three types of representations: 1) Unmagnified Raw Pixels, 2) Phase-based Magnified Features and 3) Deep Neural Network based Magnified Features. A SVM Classifier was the used for classification. By segmenting and magnifying the essential areas of the videos, the pipeline addresses some of the challenges with real-life noisy recordings. The authors have demonstrated how different methods of segmentation as well as feature representations can aid enhance classification through a rigorous evaluation. Figure 2.5 represents the framework of the model proposed by the author.

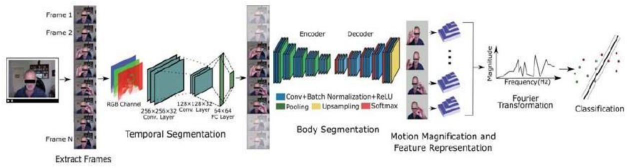

Figure 2.5 – Framework overview[10]

Research Gap

The challenges of assessing motor severity via videos are discussed in this paper, as well as the use of emerging video-based Artificial Intelligence (AI)/Machine Learning techniques to quantify human movement and their potential utility in assessing motor severity in patients with Parkinson's disease. While we conclude that video-based assessment may be a convenient and useful method of monitoring Parkinson's disease motor severity, the ability of video-based AI to diagnose and quantify disease severity in the clinical setting will require more research with large, diverse samples and further validation using carefully considered performance standards.

Challenges

The current absence of publicly available realistic datasets is the key problem when undertaking hand-tremor recognition. Short-term studies have limited the majority of research on video-based PD assessment. The long-term usage of films to analyse PD symptoms, as well as the usefulness of video-based methods in substituting face-to-face assessment, cannot be determined. The majority of current research comparing video-based and face-to-face evaluations of Parkinson's disease focuses on populations that are younger, more educated, have access to the Internet, and have milder PD symptoms.

Conclusions

Different techniques have been used by different authors and different results have been obtained. Majority of authors have work with accelerometers to provide its data as ground truth. Working with more hardware devices as accelerometer makes the experiment and solution more costly and complex to perform. In the paper, Spatio-Temporal Attention and Magnification for Classification of Parkinson's Disease from Videos Collected via the Internet[10] the author discussed a novel framework to detect PD through video recording. It addressed some major issues of noisy recording by segmenting and magnifying the relevant parts of the video. Lack of availability of dataset also hinders experiments. Research on using CNN-LSTM models to detect PD symptoms is not explored in depth yet. So, there is a scope to build PD symptoms detection/recognition systems based on CNN-LSTM.

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