
Exploring Stroke-Associated Hemiparesis Assessment with Support Vector Machines

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Abstract

Hemiparesis, the weakness of one side of the body, affects the ability of stroke survivors to move and walk. With prevalence in 80% of survivors, hemiparesis is an important measure for stroke severity. It is generally diagnosed through motor tests performed as part of the National Institute of Health Stroke Scale (NIHSS). Here we report on initial work for an alternate way of identifying hemiparesis that leverages body joint position data captured by the Microsoft Kinect v2 of people resting while waiting for the neurological examination. We employ support vector machines with 10 stroke patients and 9 healthy controls to characterize hemiparesis based on the lower core body angles of the participants, and compare our results to neurologists' diagnoses. We were able to identify left-side hemiparesis, right-side hemiparesis, or no hemiparesis with > 89% accuracy when looking at the lower body angles and observing the patients for 1 minute.

Author Keywords

Stroke, Hemiparesis, Machine Learning, Support Vector Machines, Kinect, Body-Tracking, Posture

ACM Classification Keywords

H.5.m. [Information Interfaces and Presentation (e.g. HCI)]: Miscellaneous

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Introduction

Hemiparesis refers to the partial paralysis of either the left side or the right side of the body. The most common cause of hemiparesis is stroke; roughly 80% of stroke victims experience some type of weakness of one side of the body. In particular, pure motor hemiparesis is the most common form of hemiparesis [7]. Patients who suffer from this symptom have weakness in their right or left leg or arm, and therefore have difficulty moving the corresponding limb. In order to diagnose hemiparesis, neurologists conduct motor tests as part of the National Institute of Health Stroke Scale (NIHSS) to determine not only whether a stroke patient suffers from the symptom but also the severity of the weakness. While the motor tests have been found to have strong inter-rater reliability [4], they require an experienced neurologist to conduct them. Stroke evaluation as performed by a skilled neurologist limits its application to specific clinical situations, i.e. when neurologists can be physically present. In fact, during emergencies in the field, diagnosis by emergency medical services of stroke is often no better than 50% accurate [5]. Stroke assessment and thus treatment are currently hindered by human analysis. Patients have to wait to be evaluated by an experienced neurologist at the hospital before being administered Recombinant Tissue Plasminogen Activator (rt-PA), the only FDA-approved therapy for stroke. It is for this reason that rt-PA is utilized in less than 5% of acute strokes due to the narrow therapeutic time window for intervention, within 3 hours of the onset of symptoms [2].

Efforts have been made to more quantitatively and reliably analyze hemiparesis without the need of a neurologist, particularly by analyzing gait. Computational methods to analyze ambulatory activity using wearable three-axis accelerometers, reflective markers and motion cameras [3] and ankle-mounted step watch activity monitors have all

been shown to repeatably and reliably assess hemiparetic gait. These techniques were designed to monitor hemiparetic stroke patients outdoors or at their residence, and therefore do not require the presence of a neurologist. Unfortunately, these approaches focus on rehabilitation in the long-term, with the goal of monitoring improvements in movement and gait in recovering stroke patients, rather than diagnosis in the short term. Furthermore, they require a device to be worn by the patient, which can be obtrusive. These wearables have spatial constraints and need to be specially fitted to each individual, making them suboptimal for the emergency settings in which we are interested.

To overcome this problem, in this paper we present a means of determining hemiparesis in an unobtrusive way. Our approach is based on a method that can in the future be implemented in emergency medical settings for diagnosis soon after the incidence of stroke, and without the need of an experienced neurologist. This work is based on the hypothesis that body posture, particularly when sitting, is a meaningful metric for diagnosing hemiparesis in patients.

Methods and Data Collection

In collaboration with a team of neurologists, we recruited 19 patients that were seen at the UC San Diego's Stroke Center in the period right after being diagnosed of acute stroke. All participants in the study agreed to be recorded with sensors by signing a consent form approved by the local Human Research Protections Program office. We leveraged Kinect v2's ability to automatically capture the movement of 25 distinct body joints and their orientations in 3-dimensional space to deliver a real-time body skeleton for each recorded individual in the depth camera's field of view. Data was collected using the ChronoSense software [6], at a body tracking capture rate of 30 Hz. The 19 patients were divided into 10 stroke patients and 9 healthy controls, the



Figure 1: Body tracking data collected from a patient during a neurological assessment by the Kinect. Top: The patient here is shown sitting at rest prior to the start of the NIHSS examination. Bottom: Representation of the body through the Kinect v2 joints.

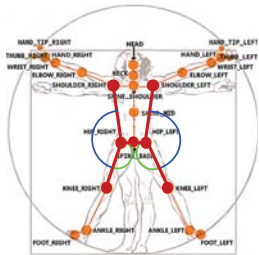


Figure 2: In blue and green we highlight the 4 lower body angles analyzed in this study.

latter of whom either did not have a stroke or were seen for stroke but have since fully recovered and so exhibited no stroke-associated symptoms. Participants were recorded by the Kinect v2 at a distance as they were simply sitting and waiting for the neurologist, at rest. All patients were diagnosed as having left-side hemiparesis, right-side hemiparesis, or no hemiparesis (control) by an expert neurologist through routine clinical examination with the NIHSS. Figure 1 shows an example of the collected data visualized using ChronoViz [6].

To account for the differences in heights, physicality, and the body skeletons mapped by the Kinect between participants, we monitored body angles, a metric that is relative to each participant and that can be compared between participants. We performed our analysis on both lower core body angles, upper core body angles, and a combination of both (see Fig. 2). We focus here on only the results from the analysis of lower body core angles, which resulted on the greatest classification accuracy.

For each participant, we computed the average of the 4 lower body angles during their resting time, the time prior to the start of the NIHSS test when the patient was simply sitting and waiting. After considering the spread of resting times in our data, the typical time-scale of human body movements, and possible applications of real-time detection of hemiparesis in emergency settings, we average the body angles of patients over one minute; for patients with resting time < 1 min we considered their total resting time. Because the NIHSS has not yet started, body movements during the resting time are limited and the body angles that we are considering for posture detection do not show large changes in this period. Each participant therefore has a single set of 4 body angles averaged (normalized) over 1 minute of the resting time. Because we are no longer dealing with time series of dynamically changing body angles

and are instead working with a set of averaged, discrete body angles, our machine learning approach was greatly simplified.

We analyzed the set of 4 averaged body angles for each of the 19 patients using a support vector machine (SVM) classifier with a linear kernel type [1] and compared this with the neurologist's hemiparesis assessment as our ground truth. Neurologists' diagnoses of hemiparesis through NIHSS motor tests have strong inter-rater reliability [4], and therefore we are not concerned with the subjective nature NIHSS for this particular stroke symptom.

Because of the limited sample size - 9 controls, 5 patients with left-side hemiparesis, and 5 patients with right-side paresis - we used a *leave-one-subject-out cross validation (LOSOXC)* technique to train our SVM. We trained our SVM classifier with 18 of the participants, with 1 participant used to test the classifier. We repeated this process and rotated this 1 test participant so that every participant in the study was used to train the classifier 18 times and used to test the classifier once. For each of the 19 tests, we obtain a predicted label (left-side weakness, right-side weakness, or no weakness) which we then can compare to the actual, ground truth label. Because we used LOSOXC, the accuracy of a correct prediction for a subject is 1 and an incorrect prediction was 0. Overall classification accuracy was computed by averaging these 19 prediction accuracies.

Results and Discussion

With our sample of 19 patients, we have developed an algorithm that is able to classify left-side weakness, right-side weakness, and no weakness based on four lower core body angles with 89.47% accuracy. We were able to achieve this accuracy when we averaged body angles over up to a single minute for each patient. This is an important result be-

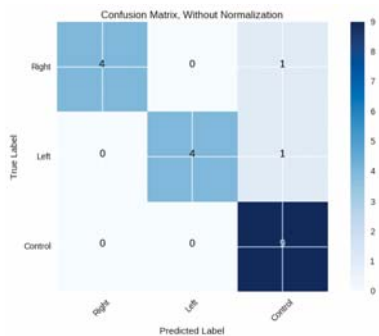


Figure 3: Confusion matrix for the SVM classification results of the lower body angles. Columns refer to the label predicted by the SVM analysis, while rows are the real condition of the patients, as determined by an experienced neurologist.

cause it shows that all a patient needs to do is sit at rest for one minute for our algorithm to detect hemiparesis with high-accuracy; this will make implementing the algorithm in busy emergency rooms more feasible.

As can be seen in Fig. 3, false negatives are few. Additionally, the algorithm does not overlook left-side or right-side hemiparesis, and there are also few false positives. Finally, the algorithm does not mistake a healthy control participant as having weakness. In the setting of medical diagnostics, having few false positives is especially important to avoid prescribing treatment to an healthy individual. We report an F1 score of 0.894. (We used a weighted average when computing the F1 score to account for the data size imbalance between the three classes.) Continuing to enroll stroke patients will enable us to use more sophisticated machine learning approaches to characterize hemiparesis across the severity spectrum, from mild to severe.

In summary, we showed that using SVMs to diagnose hemiparesis based on patient body posture is feasible. The fact that we are able to do this while a patient is simply sitting is exciting because it allows us to implement our algorithms in emergency settings where patients are not likely to move too much. Gait analysis in ambulances or in the emergency department, for example, is difficult. We believe that our method is also less obtrusive than wearable accelerometers, and does not need to be tailored to each patient because body angles are relative to individuals and can be compared across them.

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