Towards Remote Evaluation of Movement Disorders via Smartphones

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***Abstract*— Recent advances in mobile phone technology have placed an impressive array of sensing and communication equipment at the hands of an ever-growing number of people. One of the areas which can potentially be transformed by the availability of what is essentially a cheap, ubiquitous networked sensor, is that of remote diagnosis of movement disorders, such as Parkinson's disease. This work describes a smartphone-based method for detecting and quantifying the hand tremor associated with movement disorders using signals from the accelerometer and gyroscope embedded in the patient's phone. Our approach is web-based and user-friendly, requiring minimal user interaction. In clinical experiments with twenty subjects, we found that by combining both accelerometer and gyroscope signals, we were able to correctly identify those with hand tremor, using very simple signal metrics.**

I. Introduction

HUMAN expertise is heavily relied upon when it comes to evaluating movement disorders, such as those caused by Parkinson's disease. Parkinson's affects approximately 1% of the population over 60 years of age and is characterized by abnormal movement, including involuntary resting hand tremor. One clinical method used to quantify the symptoms is the unified Parkinson's disease rating scale (UPDRS) [1], which involves observing the patient in various postures and "standardized" movements, and "grading" their performance on a scale of 0-4. Although from the point of view of medical practitioners this face-to-face interaction is very "rich" in information, it is nevertheless a subjective exercise. This gives rise to the need for quantitative methods for evaluating movement disorders, as a complement to the clinical examination. Efforts in that direction have typically relied on the use of special hardware and various body-mounted sensors, such as accelerometers; however, the advent of so-called "smartphones" has now placed much of the required instrumentation at the hands of an ever-growing number of people worldwide. This creates intriguing possibilities for phone-based applications which can quantify movement disorders, for the purpose of aiding the physician's diagnosis and for tracking the progress of the patient's condition. Furthermore, such devices can be used virtually anywhere, with the results communicated to the physician remotely. The latter is an especially important consideration, given the significant amounts of time and medical resources required for a clinical evaluation.

This paper's contribution is a smartphone-based diagnostic tool for the detection and tracking of movement disorders, which quantifies a patient's condition by combining data from the phone's accelerometer and gyroscope. We are specifically interested in obtaining both acceleration and rotational velocity data because observations of patients with movement disorders show that tremor in their upper extremities (e.g. hand) may have a significant rotational component. The required software is web-based, requires minimal user interaction and no technical expertise. Our experimental platform was used with an iPhone to detect hand tremor in a clinical setting involving ten healthy subjects and ten subjects with movement disorders. We found that when using both accelerometer and gyroscope signals, we were able to correctly categorize the subjects with movement disorders, using very simple signal metrics.

II. Background

During the past few years there have been several efforts to establish computer and sensor-assisted methods for evaluating Parkinson's disease [2]. In some cases [3], [4], wearable sensors were used to record signals which are then transmitted to a computer. Other examples include [5], [6] and the Kinesia™ [7] application. In most of these approaches and in other quantitative clinical tests currently in use, the subject must wear specially-designed hardware, which may be expensive and typically requires some technical expertise to use. Moreover, the wireless range of the devices used is limited; thus data must be sent to a local station, necessitating additional equipment and processing if it is to be used for remote evaluation or diagnosis.

A more recent approach [8] took advantage of the accelerometer and wide wireless coverage range provided by an iPhone 3G. In that work, an iPhone application ("app") collects the acceleration data when the device is worn by the user and sends the data to a remote station via e-mail, thereby eliminating specialized hardware and wireless

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coverage constraints. Here, we use [8] as a point of departure towards the remote detection of movement disorders via smartphones. The advantages of our method include i) being web-based (i.e., does not require the user to install an application, such as [9], which consumes phone resources), thus accessible by a wider range of devices, ii) making use of the on-board gyroscope (in addition to the accelerometer), which improves our ability to detect hand tremor using very simple signal metrics and criteria, and iii) user interaction that is essentially reduced to the push of a virtual button, without the need for further handling the data or sending it manually via email.

III. Experimental Setup & Software

Our setup consists of four essential components:

1. An iPhone 4 with iOS 4.2 or later, with Internet access enabled,
2. A web site which collects data from the phone's sensors when visited by the user,
3. A web server which hosts the site and stores measurements,
4. Software for processing the signals received at the server.

Our web-based application is intended for use on any phone equipped with an accelerometer and a gyroscope. We expect that by combining acceleration and angular velocity data we may be able to improve detection of movement disorders by accessing rotational components of hand tremor. We chose to experiment with the iPhone because its operating system, iOS 4.2, incorporates Javascript APIs which make it possible to read the phone's sensors through a website. That means that in order to read an iPhone's 3-DOF acceleration, a_x, a_y, a_z, orientation, $\theta_x, \theta_y, \theta_z$, and angular velocity, $\omega_x, \omega_y, \omega_z$, one may simply build a website and ask the user to visit it, which is what we have done.

A web-based interface also makes our approach platform independent. The trade-off is that the necessary APIs [10] are currently available only in iOS 4.2; however, there are indications [11] that other smartphone operating systems, (e.g., Android) will eventually support the same interface.

The website we set up to collect the data can be hosted by any web server running php. A screenshot is shown in Fig. 1. The website's size (what the user will download) is only about 10 KB. The site is currently used to support small-scale clinical tests, and can be accessed at [12]. The data are automatically posted and saved on the server (in text files of less than 40KB, typically), without having to store them locally in a file which the user will then sent by e-mail.

Operationally, a user who wants to perform a measurement must have internet access enabled on their phone, and screen orientation must be "locked" to avoid mislabeling the data. The user then visits the website, optionally enters a few pieces of information (see Fig. 1), and then clicks on a link to start transmitting accelerometer and gyroscope data to the site. After a delay of 3 seconds, to allow the user to position the device as desired, data are

Fig. 1. A screenshot of the website, as shown on the iPhone. The user can optionally fill in their name, the type of movement they want to execute and specify the hand used (left or right). When the site is visited, a php session is created to access the on-board hardware and collect data. Each time a measurement is completed, the user is redirected back to this page.

collected for 12 seconds and then automatically submitted to the server, where they are saved in a file. The user is then redirected to the initial page, and may perform additional tests. At the server, the data are processed to extract information about possible movement disorders. Currently, that processing is done via a separate MATLAB application; however, our plan is to integrate its execution into the website, so that the results may be automatically obtained and communicated back to the user and/or their physician.

IV. Data Collection & Analysis

To proceed with data collection we designed a custom mounting glove for the phone using a wrist protection glove and a hard case for the device (see Fig. 2). It is possible to forgo the glove and have the user simply hold the phone.

Fig. 2. Photo of the custom made glove-case with an iPhone mounted on.

However, in the initial stages of this work we wanted to standardize the phone's posture as much as possible and to eliminate any possible effects from the action of the fingers gripping the phone. The phone was worn by 10 healthy control subjects, referred to as the Normal (N) group, and 10 patients, referred to as the Movement Disorder (MD) group, recruited from the outpatient clinic of the 1st Department of Neurology at the Aristotle University of Thessaloniki. All subjects agreed to participate in this research after a detailed explanation of its aims and of the testing procedure. Subjects 1-8 in the MD group were Parkinson's patients. Subjects 9

and 10 suffered from cerebellar and psychogenic tremor, respectively. All MD subjects were under medication.

During clinical tests, subjects were asked to wear the iPhone on their wrist, and sit with their arms extended horizontally in front of them, keeping that position for 12 seconds while data were recorded. The device was mounted on both their hands alternately, and each test was repeated at least twice for each subject. From the data obtained, we formed the subject's acceleration vector, $\alpha(i) = [\alpha_x(i), \alpha_y(i), \alpha_z(i)]^T$ (in m/s^2) and angular velocity vector $\omega(i) = [\omega_x(i), \omega_y(i), \omega_z(i)]^T$ (in rad/s), with i denoting discrete time. Typical profiles of the two vectors (magnitude squared) are shown in Fig. 3.

One challenge when using the iPhone's current Javascript APIs is that the sampling rate (or rate at which the API may be triggered) is not adjustable, and stays at a default 20Hz, which is quite low. Furthermore, sampling of the on-board devices via JavaScript is subject to jitter (in some cases we measured a jitter of up to $5ms$ with a nominal sampling period of $50ms$). In light of these considerations, we chose to explore very simple signal metrics (e.g., energy or power) for categorizing subjects as to whether they exhibited hand tremor or not. Specifically, we computed

$$m_\alpha = \frac{\sum_1^N \|\alpha(i)\|^2}{N} \quad \text{and} \quad m_\omega = \frac{\sum_1^N \|\omega(i)\|^2}{N}, \qquad (1)$$

where N was the number of samples in the signal, and attempted to categorize subjects based on these two quantities. Here m_α and m_ω can be viewed as signal power, the signal being the length of the acceleration and rotational velocity vectors, respectively. Typical values of these metrics when the iPhone was at rest on the desktop were $m_\alpha = 0.0127$ and $m_\omega = 0.0000$.

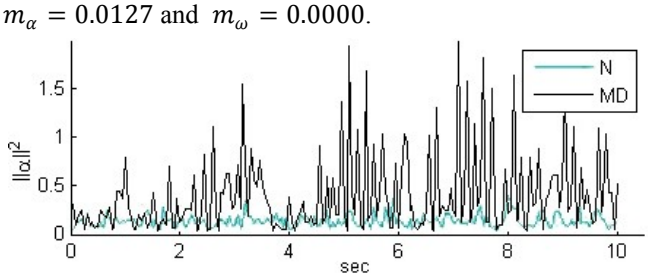

Fig. 3a. Acceleration (magnitude squared) for a control subject compared to a Parkinson's patient.

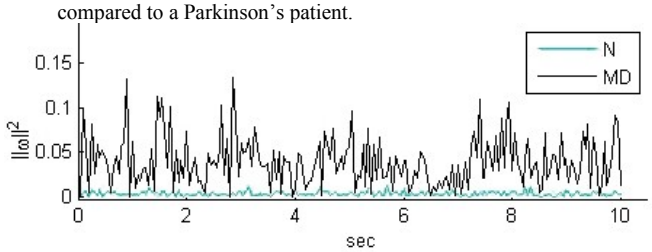

Fig. 3b. Rotational velocity (magnitude squared) for a control subject compared to a Parkinson's patient.

A. Comparisons

We first compared the mean values of the two metrics for our two populations, using all data (left and right hand) for each subject. The N population had an average acceleration power of 0.0915 (min=0.0338, max=0.1325), which was low compared to the MD mean of 0.1760. Statistical analysis (Mann-Whitney test) verified that differences between two populations were indeed significant. With respect to angular velocity power, the N population had a mean of 0.0039 (min=0.0020, max=0.0066), while the average for MD subjects was a much higher 0.0224. The 10th MD subject's scores were much higher than the rest, and were excluded when calculating the mean for the MD group, in order to avoid "artificially" strong comparisons with the N group. As depicted in Figure 4, all MD subjects scored higher than the N-group (control) mean when considering the m_ω metric (in 4 cases they scored higher in both metrics).

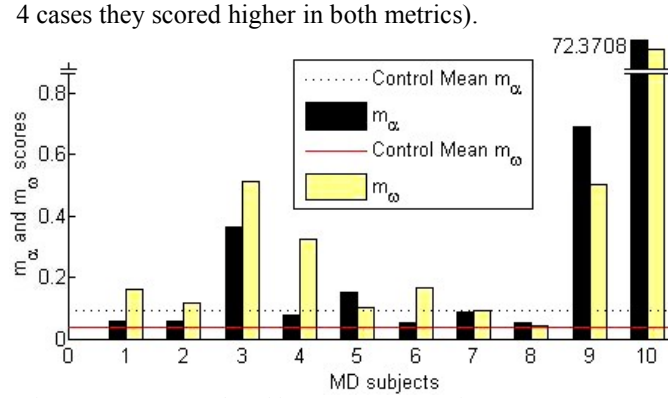

Fig. 4. Bars represent the subjects' mean scores using measurements from both hands. m_ω scores are scaled by 10.

The acceleration and angular velocity metrics we computed, generally agreed with the severity of hand tremor as observed clinically. Because of space constraints we only present data for the MD group as compared to the mean and maximum values from the N group. The corresponding data for the healthy subjects can be found in [13].

One of our goals was to see how well we can detect movement disorders (in this case, hand tremor) using m_α and m_ω. Towards that end, we explored the possibility of identifying subjects with hand tremor via two simple criteria. The first was whether either of a subject's mean measurements (m_α, m_ω) were above a certain threshold, namely the highest mean score encountered in the N group. Because it is known that movement disorders typically affect one side of the patient more severely than the other, we re-calculated each metric using data only from each subject's "worst" hand, i.e., the hand which scored highest in each metric. By doing so, the highest acceleration and angular velocity scores for healthy subjects were 0.1515 and 0.0092, respectively. The identification of patients' worst performing hands by comparing average metrics for their left vs. right hand as described above, gave the same results regardless of the metric used (acceleration or rotational velocity), and correctly identified the worst hand of every patient except subject 4. The comparisons between the subjects' mean scores for their worst-performing hand and the thresholds (maximum scores) obtained from the N group are described in Figure 5. The thresholding criterion correctly "labels" nine of the ten subjects as being in the MD group. The one exception was subject 8 who does suffer from Parkinson's

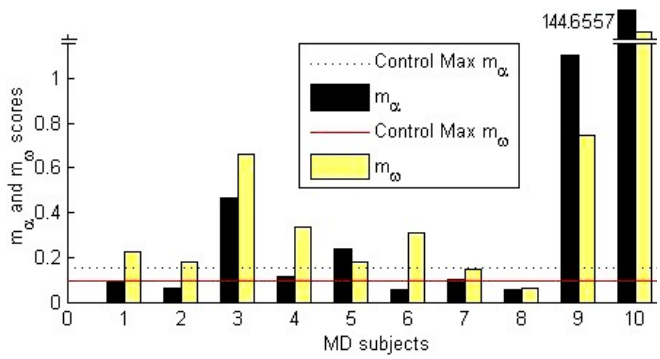

Fig. 5. Bars represent the subjects' mean scores using measurements only from worst performing (highest- scoring) hand. m_ω scores are scaled by 10.

disease, but his symptoms include mostly bradykinesia and rigidity, as opposed to pronounced hand tremor. We note that if we were to judge based on m_ω alone, then the same nine subjects would be categorized as MD, whereas only four subjects exceeded the m_α acceleration threshold.

A second criterion for comparing the MD and N populations was the difference in m_α (and m_ω) between hands. A healthy subject is not expected to have very different left vs. right mean scores, while the opposite is often true for patients with movement disorders. The control group (N) had an average hand-to-hand difference of 0.0232 in m_α (max=0.0514, min=0.0123, std. dev.=0.0117) whereas MD subjects had an average difference of 0.1572 (std. dev.=0.2629). The corresponding numbers for m_ω were 0.0031 (max=0.0053, min=0.0006, std. dev.=0.0016) for the N group and 0.0185 (std. dev.=0.0147) for the MD group. Again, nine of the MD subjects had mean differences which exceeded the maximum encountered in the N group in either m_α or m_ω, or both; they were the same nine identified via thresholding on worst-hand scores (see [13] for individual scores).

V. Conclusions and Ongoing work

We explored the use of recently-available smartphone technology for the purpose of diagnosing and quantifying the postural tremor which characterizes movement disorders such as Parkinson's disease. Our method is based on the use of on-board accelerometer and gyroscope which are currently found in many smartphones and can be accessed via the web. Unlike previously proposed approaches, ours i) is web-based, meaning that the user simply visits a web page without installing software on their phone, or handling the data being collected, and ii) uses accelerometer and gyroscope data simultaneously in order to classify patients based on very simple signal metrics and thresholding.

We tested our approach in a small clinical trial involving twenty subjects (half of them being the control group) and found that we correctly categorize nine of the ten patients, based on the power of their acceleration and rotational velocity signals, or the differences in performance between their two hands. The gyroscope data appear to be particularly useful in that regard.

Our goal is to ultimately make our web application freely available on a dedicated server which will receive data and return the results to the user and their physician (securely, over SSL), for the purposes of providing remote diagnostic decision support and tracking of the patient's condition over time. Towards that end, we are currently in the process of evaluating our approach in larger trials, with data obtained from additional types of subject movements and postures, alternative signal metrics, and comparison of the resulting scores to the patients' UPDRS ratings.

The fact that we are using a JavaScript API to control the smartphone's hardware (as opposed to its native programming platform) does give us flexibility but deprives us of certain benefits such as adjusting the sampling rate. To circumvent this problem, we are also pursuing an Objective C application which will be used to repeat the same clinical tests for comparison, as well as more sophisticated signal processing methods (including reconstruction for irregularly sampled signals [14], [15]).

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