A Method to Detect Keystrokes using Accelerometry to Quantify Typing Rate and Monitor Neurodegenerative Progression

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Abstract: Progressive motor neurodegenerative diseases, as ALS, cause progressive loss of motor function in upper limbs. Motor involvement, also affecting speech at some stage of disease, cause increasing difficulties in accessing to computer devices (and internet tools) that allow communication with caregivers, and healthy professionals. Thus, monitoring progression is important to anticipate new assistive technologies (AT), e.g. computer interface. We present a novel methodology to monitor upper limb typing task functional effectiveness. In our approach, an accelerometer is placed on the index finger allows to measure the number of keystrokes per minute. We developed algorithm that was accurate when tested in three ALS patients and in three control subjects. This method to evaluate communication performance explores the quantification of movement as an early predictor of progression.

1 INTRODUCTION

Quantitative assessment of the motor performance of human body has raised important questions and scientific findings in last decades. Modern technology allows to study movement using miniaturized and wearable equipment. Namely, accelerometers used as clinical tools, are broadly used to monitor daily activity and tremor, specially in movement disorders (Bonato, 2003; Godfrey et al., 2008). In context of progressive diseases, monitoring tools that can be used in the daily living are important to track progression and adjust treatments and interventions (Shany et al., 2012; Bustamante et al., 2011).

The use of computer devices as assistive technologies (ATs) for Communication is very important concerning quality of life in some neuromuscular diseases that affect speech or writing abilities. Particularly in Amyotrophic Lateral Sclerosis (ALS/MND), patients experiment progressive loss of speech and limbs motor function and consequent difficulties in communicating without ATs (Korner et al., 2013; Beukelman et al., 2000). Access to computer devices is also important to give access to eHealth services for patients.

Although speech progression in ALS has been studied for the purpose of monitoring communication needs (Ball et al., 2002), writing function (as upper limb motor progression) has been underestimated as a variable for monitoring communication abilities of ALS patients. ATs for communication are commonly based on electronic devices and typing tasks (considering the use of text-to-speech technologies), either on a physical keyboard or a virtual keyboard accessed via touchscreen. Due to the neurodegenerative characteristics, it is important to follow symptoms of progression in upper limb motor control to identify periods to adapt or introduce ATs, aiming at augmenting users' functionality in communication (Beukelman et al., 2011; Bongioanni, 2012).

In this study, we aim to investigate the potential of monitoring progression of upper limb motor functionality needed to perform typing tasks on a keyboard. For this purpose, we captured data from a 3D accelerometer placed on the index finger (finger used to press the keys) and captured a 10-word typing task. In this paper, we describe the

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methodology and the developed algorithm to detect and quantify keystrokes events from accelerometer signals captured during the experiments. As first results, we present data from three ALS patients and from three control subjects (with no diagnosed neurological disease).

The rest of the paper is organized as follows: Section 2 describes methodology used to acquire data from accelerometer; Section 3 describes the proposed algorithm for typing detection; in Sections 4 results from data analysis are presented; Section 5 and 6 present discussion and main conclusions on the first results of this study.

2 METHODS

2.1 Participants

We present results from 3 patients with ALS and 3 healthy control subjects. ALS patients (2 women and 1 man) had a mean age of 53 years old (37, 59 and 63 years old). At baseline assessment, all participants with ALS had clinical evaluation of ALSFRS-r (Cedarbaum et al., 1999) speech subscore less or equal to 2, though all were able to use upper limbs to type on a keyboard. Patients had no dementia. Healthy control subjects (2 women and 1 man) had mean age of 32 (23, 35 and 37) years old.

2.2 Equipment

For accelerometry acquisition a Bioplux Research system (PLUX SA) was used. In our research settings, we used the system with a 3-axial MEMS accelerometer sensor *(*±3g measurement range). Sensor was placed in exterior part of index finger of the functional hand, as depicted in Fig.1. The three axes were measured according to Fig.1 in directions: anterior-posterior(X), distal(Y) and lateral(Z). Data was sampled at 1KHz. Data was acquired via Bluetooth to a laptop computer to be later processed using *Python* tools. A second laptop was used by the participants to perform the typing tasks.

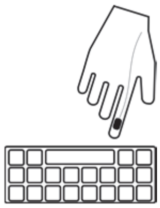

Figure 1: Index finger for typing.

2.3 Procedure

Subjects were asked to type a 10-word sentence using just the index finger. Accelerometer was placed in the finger and data from the accelerometer was saved. The same accelerometer sensor was always used. Patients were evaluated in 3 sessions, in 3 months intervals. Control subjects just performed one trial in one session, as no progression is expected for control participants. A camera was also used to capture typing task, for results validation.

Figure 2: Photo from an evaluation.

2.3.1 Outcome Measures based on Accelerometer

For simplification, we used Y axis (distal movements of index finger) to characterize typing function, as this is the direction related to the movement of pressing keys (as illustrated in Fig 1). As outcome variables we wanted to have *number of keystrokes*, *typing rate*, *time between keystrokes*, *time duration of each keystroke*, *amplitude of acceleration signal (*amplitude of acceleration of finger movements in distal direction), *magnitude of acceleration signal (*calculated as the Euclidean vector for the 3-axis acceleration signal).

2.4 Algorithm for Typing Detection

We analysed accelerometer signals from patients and control subjects. Key types from the 10-word sentence were analysed. Fig.3 shows the plot from the acceleration signal of one of the control subjects, illustrating a set of keystrokes and one isolated keystroke.

An algorithm was developed to extract outcome variables from each typing task.

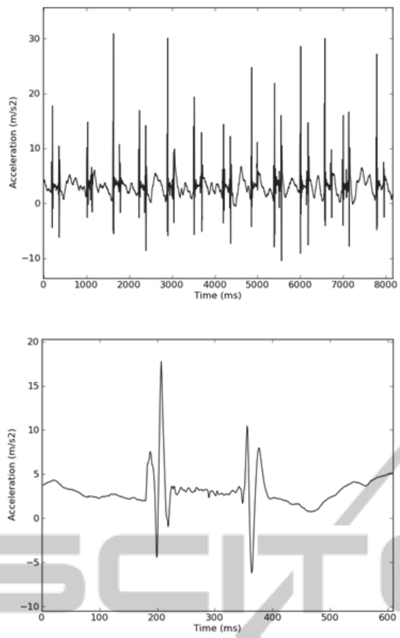

Figure 3: Plots from keytyping from a control subject. (up) Set of 13 keystrokes (down) One keystroke: first acceleration pulses correspond to press action and the second acceleration pulses correspond to release action.

2.5 Characterization of a *Typing* Action

For the setup suggested in this paper, a keystroke (for simplicity, we consider signal from Y-Axis to analyze movements in distal direction) is characterized by two *events* of acceleration (Figure 3). The first *event* is related to pressing action and the second *event* is related to releasing action.

2.5.1 Signal Processing for Detection of Typing Actions

Proposed algorithm first removes DC component from acquired data, then uses a moving average algorithm to smooth the signal's module (Figure 4). From the processed signal, peaks are detected (from a threshold value calculated as a factor of maximum amplitude) as events of pressing and releasing keys – each group of two near peaks corresponds to the signal of a keystroke.

Due to erroneous movements (from video analysis we could identify hand gestures performed during typing task or touching a key with no pressing action) two kinds of peaks were detected as frequent false typing events:

- isolated event: isolated peaks or a peak close to a pressing event (video analyses show that a single peak may occur when user touches a key but doesn't press it – this is caused by a hesitation (commonly caused by low experience in the use of a qwerty keyboard);

- third event: we could observe in the acquired signals frequent low amplitude acceleration impulses prior to a typical keystroke signal. From the video analysis we could conclude that these acceleration impulses are due to slow typing (an evident delay between touching the key and pressing it).

To guarantee a pair number of peaks (press/release keys), previously described false typing events were removed: signal was analysed near each detected peak of acceleration. Isolated events were eliminated and, in groups with more than two close events, only the two with higher amplitude values were kept.

Keystroke events detected with the proposed algorithm are depicted in Fig 5.

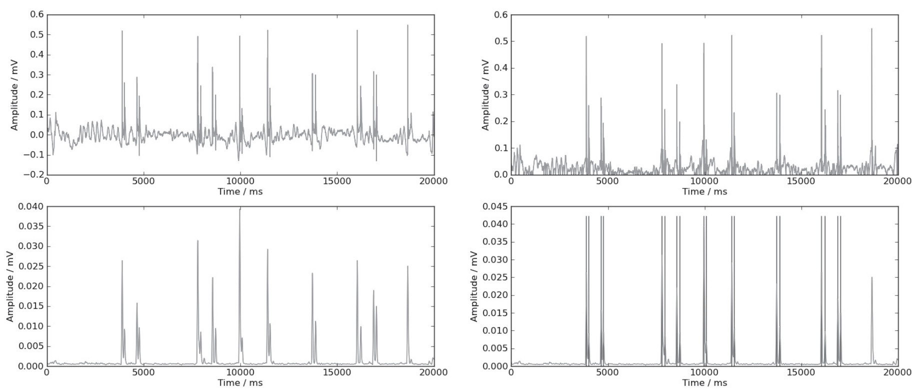

Figure 4: (top left) raw signal; (top right) signal's module; (bottom left) filtered signal using smooth algorithm; (bottom right) bottom left signal and vertical lines representing peaks detection. All schematic representations are of 20s of samples from one patient performing a typing task.

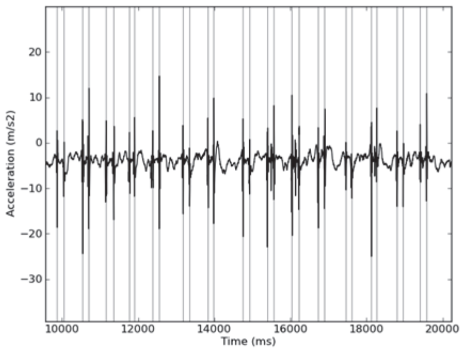

Figure 5: Representation of keystrokes detected from approximately 10s of accelerometer signal acquisition (a patient performs 15 keystrokes, typing a 10-word sentence).

3 RESULTS

All collected signals were processed with the proposed algorithm. Features from typing task were calculated and are represented in Table 1. We also measured performance of typing task, presented in second column of Table 1 as *words per minute* (wpm), using visual video analysis.

We applied the algorithm to the signals of control subjects and patients (different users and three different periods during disease progression).

As can be observed in Table 1, in spite all subjects were asked to do the same typing task, the number of keystrokes performed in each typing task (#ks) is not always the same. This is due to variability among subjects experience. For example, some of the patients forgot to add spaces between two different words, some added more than one space or used the backspace to correct a mistake. One of the patients (patient P1, in Table 1) had no experience in using computer devices, the reason why we reduced the sentence to 5 words (half of the sentence). In fact, as it is not the aim of this study to evaluate the written text, participants had no specific constraints (related to text) when performing the typing task.

From visual observation of accelerometer plots, a validation of the algorithm was performed, based on a manual adjustment of the algorithm variables (i.e. threshold value for peak detection and time window to search for false events). Number of keystrokes detected by the algorithm was confirmed with the number counted in video observation. Results are presented in Table 1. We calculated a Pearson correlation of 0.98484 between *words per minute* (obtained from video analysis) and *keyrate* (result of proposed algorithm from accelerometer analysis) for the set of all analyzed data. These results validate the used methodology to performance evaluation.

4 DISCUSSION

Finding methodologies that can early predict progression allows a faster and customized response of interventions and care. We hypothesized there is a relation between user performance on typing tasks (measured as communication speed - *wpm*) and respective kinematic analysis of typing and that this can provide a more sensitive tool to detect progression in upperlimbs motor function. A methodology to collect data from a 3-axis accelerometer placed on the index finger was developed for typing task.

A set of data captured from healthy subjects and ALS patients (in different time periods) was analyzed. Presented results show that keystrokes detected from the developed algorithm had high correlation with performance measured by video analysis. Although, high accuracy was due to fine adjustment of two parameters, which had to be manually adjusted for each data set. It was not possible to establish a peak threshold common to all studied signals – it had to be manually adjusted within different users or along different samples from the same user. Also, using the suggested algorithm, it was difficult to distinguish very low amplitude peak from noise or involuntary movement – window size to remove false events had to be manually adjusted for each sample.

From a preliminary analysis of the results presented in this paper, we could observe that, for ALS patients, in spite performance values in different periods of evaluation are variable (we can't always find evident decrease in time), the maximum amplitude of y-axis signal ($V_Y$máx, Table 1) and the mean value of the amplitude of magnitude signal (last column in Table 1) always decrease along the different time periods of evaluation (3 months interval, approximately). Although careful analysis is part of future work for the presented study, these preliminary results suggest a new surrogate marker of typing function deterioration, potentially more accurate than simple typing performance observation.

5 CONCLUSIONS

In this paper we present an algorithm for studying

Table 1: Results from the analysis of acquired data with the algorithm proposed for typing detection. Each row describes the results from control subjects (C_i) and patients (P_i) in the different evaluation times (T_i). #ks – number of keystrokes; µ tbt_key – average of time interval between keystrokes; µ tkey – average time duration of keystrokes; VYmáx – maximum amplitude of Y-axis of accelerometer signal; Magn. Máx – maximum amplitude of magnitude of accelerometer signal; Magn.Mean – mean magnitude of the accelerometer signal).

Particip.	wpm (video)	keyrate	# ks	total time (s)	µ tbt_key	µ tkey	$V_Y$máx (mV)	Magn. Máx (mV)	Magn. Mean µV
C1	10	43	43	60	331.8	75	623.79	220.12	60.99
C2	10	44	44	60	852.1	244	253.44	151.91	32.65
C3	10	44	44	60	1011.4	144.5	299.53	192.05	31.18
P1.T0	3.04	13.17	18	82	3952.2	255.1	623.43	149.26	40.68
P1.T1	3.1	11.46	17	89	4819.4	186.6	555.29	314.36	33.6
P1.T2	3.87	12.00	13	65	4129	241.5	412.22	195	31.44
P2.T0	16.66	67.89	43	38	527.6	168.1	624.19	147.34	38.34
P2.T1	16.61	62.67	47	45	669.9	188.5	475.47	225.08	36.62
P2.T2	17.3	61.82	44	42.7	666.1	252.5	427.32	129.08	33.72
P3.T0	7.69	28.53	39	82	1282.3	712.8	495.77	212.19	42.64
P3.T1	9.38	33.75	45	80	736.3	847.1	480.26	177.54	32.35

typing performance through accelerometry.

A 3-axis accelerometer was placed in the index finger of 6 participants (3 with progressive neuromuscular disease and 3 healthy participants). Signal processing of the accelerometer signals showed high correlation between independent measures of performance: words per minute (from video analysis) and keystrokes per minute (from accelerometer).

Presented algorithm should be improved to automatically adjust all the parameters for different users and different stages of progressive disease. As future work, a detailed analysis of other parameters of accelerometry, independent from performance measures, should be done.

REFERENCES

Ball, L. J., Beukelman, D. R. and Pattee, G. L., 2002. Timing of speech deterioration in people with amyotrophic lateral sclerosis, *Journal of Medical Speech-Language Pathology*, 10(4), 231–235.

Beukelman, D., Fager, S. and Nordness, A., 2011. Communication Support for People with ALS. In *Neurology Research International*, Article ID 714693.

Beukelman, D. R., Yorkston, K. M., Reichle, J., 2000. *Augmentative and Alternative Communication for Adults with Acquired Neurologic Disorders.* Brookes H. Paul Publishing, Baltimore.

Bonato, P., 2003. Wearable sensors/systems and their impact on biomedical engineering. In *IEEE Engineering in Medicine and Biology Magazine*, 22(3), 18–20.

Bongioanni, P., 2012. Communication Impairment in ALS Patients: Assessment and Treatment. In Maurer, M. (Ed.) *Amyotrophic Lateral Sclerosis*. Available from: http://www.intechopen.com/books/amyotrophic-lateral-sclerosis.

Bustamante, P., Solas, G. and Grandez, K., 2011. Neurodegenerative Disease Monitoring Using a Portable Wireless Sensor Device. In Chang, R. (Ed) *Neurodegenerative Diseases - Processes, Prevention, Protection and Monitoring*, InTech Publisher. Available from: http://www.intechopen.com/books/neurodegenerative-diseases-processes-prevention-protection-and-monitoring.

Cedarbaum, J. M., Stambler, N., Malta, E., Fuller, C., Hilt, D., Thurmond, B., Nakanishi. A., 1999. The ALSFRS-R: a revised ALS functional rating scale that incorporates assessments of respiratory function. BDNF ALS Study Group (Phase III). In *Journal of the Neurological Sciences,*169(1-2),13-21.

Godfrey, A., Conway, R., Meagher, D. and ÓLaighin, G., 2008. Direct measurement of human movement by accelerometry, In *Medical Engineering & Physics*, 30, 1364–1386.

Korner, S., Siniawski, M., Kollowe, K., Rath, K.J., Krampfl, K., Zapf, A., Dengler, R., Petri, S., 2013. Speech therapy and communication device: Impact on quality of life and mood in patients with amyotrophic lateral sclerosis. In *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration*, 14, 20–25.

Shany, T., Redmond, S. J., Narayanan, M. R. and Lovell, N. H., 2012. Sensors based wearable systems for monitoring of human movement and falls. In *IEEE Sensors Journal*, 12(3), 658–670.