DESIGN OF A NEUROMUSCULAR DISORDERS DIAGNOSTIC SYSTEM USING HUMAN MOVEMENT ANALYSIS

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ABSTRACT
This communication summarises the outcome of our research program on the design of a diagnostic system for neuromuscular disorders based on the analysis of human movement using the Kinematic Theory of Rapid Human Movements. Herein, this design problem is split in sub-problems which are then described. The solutions adopted at each design step are explained. As an example of application, typical results obtained so far for the assessment of the most important modifiable risk factors of brain stroke (diabetes, hypertension, hypercholesterolemia, obesity, cardiac problems, and cigarette smoking) are reported by the means of the area under the receiver operating characteristic curve (AUC).

1. INTRODUCTION
Previous researches indicates that human movement can be looked at for markers of various conditions affecting the neuromuscular system such as Parkinson disease [1,2], brain stroke susceptibility [3], multiple sclerosis [4], Alzheimer disease, cognitive impairment [5, 6], presence of upper motor neuron syndrome [7], dyspraxia [8], medication [9], etc. Hence, movement analysis can be considered for the diagnostic of medical conditions or for rehabilitation assessment [10-12].

This paper presents an overview of our researches on the development of diagnostic tools for neuromuscular disorders using the conceptual paradigm of the Kinematic Theory of Rapid Human Movement. The long term goal of such investigations is to develop low-cost and noninvasive techniques to complement or enhance more invasive and expensive (e.g. scans, electromyography, etc.) techniques already available. For example, kinematic analysis could be used as a first-line tool in clinical point of care environment, for disease screening and risk assessment before referring patients to more extensive testing.

Although some systems using movement analysis for medical diagnosis exists (e.g. MovAlyzeR by NeuroScript, Tempe, AZ, USA), to the knowledge of the authors, no system similar to the one described in this paper (including acquisition, model-based analyses, classification and AUC evaluation) has been proposed and evaluated on the brain stoke risk assessment. As such, the methodology put forward in this presentation is novel and it is difficult to compare our results with existing literature.

In the following, the Kinematic Theory is first briefly overviewed in section 2. Then, section 3 and 4 describe the design of the diagnostic system as well as the methodology used for assessing its performances. Section 5 reports some results obtained so far and section 6 concludes this communication.

2. THE KINEMATIC THEORY

The Kinematic Theory of Rapid Human Movement was first introduced in 1995 by the professor R. Plamondon [13, 14]. It has been shown to model accurately the various particularities of fast human motions like the stereotypical asymmetrical bell shapes with up to two secondary ripples that is observed on the speed profile of fast reaching motions, the mostly straight trajectory of these motions, the apparition of speed/accuracy tradeoffs, the relative consistency of the 2/3 power law, etc.

Most importantly, this theory does not only provide well-fitting models but it also defines a mathematical modeling of the human neuromuscular system with properties that are derived mathematically from premises, most of these being experimentally validated.

The Kinematic Theory considers a motion as the synergistic production of movement primitives, each of these being the result of the emission, by the central nervous system, of an impulse command. Such a command is dispatched to the neuromuscular system which is composed of a large number of complexly interconnected components (nervous cell populations, muscular cell bundles, etc.) which are assumed to work approximately linearly around their operating point. The
cumulative time delays of these components are linked through a law of proportionate effect [15]:

\[ T_i = (1 + \varepsilon_i)T_{i-1} \]

where \( T_i \) is the cumulative time delay of the system \( i \). Through the use of the Central Limit Theorem, it has been shown in [16] that, according to this modeling, the impulse response of the neuromuscular system takes the form of a scaled lognormal with a time offset:

\[ DA(t; t_0, \mu, \sigma) = \frac{D}{\sqrt{2\pi\sigma(t-t_0)}} e^{\left(-\frac{(\ln(t-t_0) - \mu)^2}{2\sigma^2}\right)} \]

(2)

Depending on the nature of the synergic relationship that is postulated between the lognormal movement primitives, different models can be considered. For a fast reaching movement, two neuromuscular systems should be considered: one pushing the end-effector toward its target and another breaking the motion. If we consider 1) that both components (agonist and antagonist to the movement) are initiated at the same time \( t_0 \), 2) that the two commands are respectively scaled by factors \( D_1 \) and \( D_2 \), and 3) that their action is directly opposed one to the other, then the velocity profile of an end-effector can be described by a delta-lognormal (\( \Delta \alpha \)) equation:

\[ \Delta \alpha = D_1 \alpha(t; t_0, \mu_1, \sigma_1) - D_2 \alpha(t; t_0, \mu_2, \sigma_2) \]

(3)

which is a one-dimensional representation of the temporal variation of the motion speed.

Oscillatory motions are slightly more complex than fast reaching ones and can be modeled in one dimension as an alternate sequence of components that are antagonist to each other

\[ \Omega \alpha = \sum_{i=1}^{N} D_{1i} \alpha(t - t_{0i}; \mu_{1i}, \sigma_{1i}) \]

\[ - \sum_{i=1}^{M} D_{2i} \alpha(t - t_{0i}; \mu_{2i}, \sigma_{2i}) \]

(4)

Such an equation is known the Omega-Lognormal model [17].

Finally, to represent truly complex movements in two dimensions such as scripting motions, a vectorial summation of components, each one acting around a virtual pivot point, can be considered:

\[ \sum \alpha = \sum_{i=1}^{N} v_{xi} \left[ \frac{\cos(\phi_i)}{\sin(\phi_i)} \right] \]

(5)

with \( v_{xi} = \alpha(t; t_{0i}, \mu_{i}, \sigma_{i}) \) and

\[ \phi_i = \theta_{ei} + \theta_{si} \left[ 1 - \frac{v_{xi}}{D_i} dt \right] = \theta_{ei} + \theta_{si} \frac{1}{2} \text{erfc} \left( \frac{\ln(t - t_{0i}) - \mu_i}{\sqrt{2\sigma^2}} \right) \]

(6)

where \( \theta_{si} \) and \( \theta_{ei} \) are the starting and ending angles of the virtual circle arc that the components would have traced if it had not been superposed to the other neuromuscular components. This representation is known as the Sigma-Lognormal model [18].

Such models can be used to compress the information of particular movements in a small set of parameters which can generally reproduce the original motion with great accuracy. Moreover, the Kinematic Theory gives a semantic to these parameters: \( t_0 \) is the moment an impulse command is generated by the central nervous system, \( D \) is the amplitude of that command, \( \mu \) and \( \sigma \) are respectively the time delay and the response spread on a logarithmic scale of the neuromuscular system reacting to that command, and \( \theta_{si} \) and \( \theta_{ei} \) are the starting and ending angles of the virtual trace of the neuromuscular component generated by that command.

3. DESIGN OF A DIAGNOSTIC SYSTEM

A computerized diagnostic tool is a specific kind of data processing systems and, like most data processing system, its workflow is mostly serial as depicted in Fig. 1. Each of these steps of the system execution requires the investigation of many design questions which are addressed in the following sections.

![Diagram](Serial_model_of_a_neuromuscular_diagnostic_system_based_on_movement_analysis.png)

**Figure 1.** Serial model of a neuromuscular diagnostic system based on movement analysis.

3.1. Data acquisition

As the modern proverb “garbage in, garbage out” tells us, there is no point in developing a diagnostic system if it cannot be fed with clean and adequate data. Therefore, much attention has to be given to the development of good data acquisition tools. Three aspects must be explored in relation to that matter: the neuromuscular task, the recording hardware, and the operating software.

3.1.1 Neuromuscular tasks

First of all, in order to get a sufficient diagnostic power, the neuromuscular tasks best at discriminating between the affected and the unaffected populations must be
The conception of new tests is known to be very time consuming since it requires a lot of efforts to assess its reliability, sensitivity, and validity. Hence, if a standard battery of tests exists for a particular diagnostic application, it will often be more interesting to use it to save time and financial resources as well as to make research results comparable with those of the literature.

However, in novel applications (e.g. the assessment of stroke susceptibility from motion analysis), such standard tests might be inexistant and it may be necessary to venture in the long term project of designing and testing a new battery of neuromuscular tasks. A theoretical framework and appropriate synthesis tools can be useful for this process, as shown in [12].

In the context of the Sign@médic project, a new battery drawing on well-known psychophysical tests has been designed. For example, it includes auditory, visual, and choice (movement to be produced in the direction indicated by an arrow) reaction time tests which have been extensively studied in the last half-century [19] as well as speed-accuracy tradeoffs derived from the task proposed by Fitts and Peterson for discrete motor responses [20]. It also includes synchronized and maximal speed oscillations, signatures, and triangle drawings. This battery has been tested on 120 subjects. The usefulness of each of these tasks for brain stroke risk assessment has been studied and recommendations are currently in preparation [17].

3.1.2 Hardware
The hardware needed for neuromuscular disorder diagnostic based on human movements depends mostly on the neuromuscular tasks that are to be used. In our case, auditory and visual reaction tests are used. Therefore, a custom stimulator which can generates beeps and visual signals using an 8 X 10 three-color (green, yellow, red) LED has been designed. Also, as the considered neuromuscular tasks require only the tracking of the upper-limb end-effector motion (e.g. trajectory of a pen tip), a 12 X 9 inches Wacom Intuos2 digitizing tablet has been used. Such a device is interesting for clinical research as it is relatively cheap, it can sample data at 200 Hz using an internal clock, it is spatially accurate (100 line per millimeter), and it is reliable. However, a USB mouse could be considered as an eventual replacement acquisition tool for an end-user product [21] (e.g. a system designed to help interested users to monitor their health condition).

3.1.3 Software
A custom software (Sign@médic) was designed in C++ to operate and synchronize the Wacom tablet and the stimulator. It also manages the experimental protocol workflow, the movement recording, and the storage of acquired data in a three level structure (sessions, trial blocks, and trials).

3.2 Motion deterministic modeling
The second step of the diagnostic process is related to the representation of the movement using the lognormal models described in section 2. In pattern recognition terms, this step corresponds to the feature extraction [22] as it allows to extract meaningful characteristics from the times series representing the recorded motion. However, the method also bears some similarity with a signal compression technique since, as opposed to most standard feature extraction algorithm, the characteristics extracted here (i.e. the lognormal parameters) contains all the information necessary to reconstruct the original signals with generally a very good accuracy. This accuracy is evaluated using the signal to noise ratio

\[ SNR = 10 \log_{10} \left( \frac{\int v_{t,n}^2 dt}{\int (v_{t,n} - v_{t,a})^2 dt} \right) \]  

(7)

where \( v_{t,n} \) is the recorded speed profile and \( v_{t,a} \) is the speed profile reconstructed using one of the lognormal models. As example, the median of the distribution of the reconstruction SNR for a maximal speed oscillations task is 27.8dB and its fitting accuracy can be appreciated on fig. 2. As can be seen, there is virtually no difference between the original signal and the reconstructed one.

Figure 2. Example of fitting accuracy between the speed profile recorded for an oscillatory motion (dotted line) and its omega-lognormale approximation (solid line).

This modeling is a key step in the analysis of human movements and it is a notoriously difficult one since the models are usually nonlinear as is the case for the lognormal models\(^2\). This is why a fair amount of the last 15 years of research on the Kinematic Theory has been devoted to the problem of developing ever better parameter extraction tools. Nowadays, reliable tools have been developed such as the IIX extractor [23] (fast and locally optimal) and a branch-and-bound extractor [24] (slow but globally optimal) for the delta-lognormal case, a prototype based extractor for the sigma-lognormal modeling of stereotypical movements [25] and the Robust XDA extractor for arbitrary complex motions [26]. As for the omega-lognormal modeling of oscillatory motions,

\(^1\) The Intuos2 could be bought for about $400 in 2002. The equivalent Intuos4 can now be bought for a similar price.

\(^2\) Indeed, the lognormals are combined linearly but they themselves have nonlinear parameters (\( t_o, \mu, \) and \( \sigma \)) which interacts with the linear parameters (\( D \)).
they are analyzed using the Robust $X_0$ estimation cascaded with a coordinate search [17]. Although not developed explicitly in the context of the Kinematic Theory, a branch-and-bound and a scattershot algorithm has also been designed by another research team for the decomposition of human motion in lognormal support bounded neuromuscular components [27, 28].

Together, these tools solve the inverse problem associated with the lognormal analysis of motions for each one of the task used in the Sign@médic project.

3.3 Population statistical modeling

This step should not be confused with the previous one. The deterministic modeling (previous section) was referring to the representation of the features of each movement sample whereas the statistical modeling discussed here is focusing on the characteristics of subject populations. This latter topic deals with two distinct processes: 1) building statistical models representing the variation of class membership as functions of the values of some preselected movement characteristics and 2) applying predefined models to a set of feature values to compute the class membership probability of a given sample.

3.3.1 Statistical model generation

This topic is more related to the design of the diagnostic system than its use. Obviously, the quality of the statistical model that will be generated (and thus, the quality of the diagnostic that they will allow) will depend on the quality of the database (e.g. its size, its representativeness of the targeted population, the quality and adequateness of the recorded signals, etc.) used for determining the proper statistical models.

The final decision of a medical diagnostic system is most often binary in nature as it is generally concerning the classification of a subject as having or not a given disease. For that matter, discriminant linear (or quadratic) analyses as well as logistic regressions are two particularly well fitting techniques [29]. As of now, both have been used with success. Although discriminant analysis seem to give slightly better results, we cannot conclude for now on the superiority of one or another from a statistically point of view. Therefore, no hasty choice have been made and both are included and tested in parallel until data indicates clearly the superiority of one over the other of the equivalence of both techniques.

There are mainly two other things that need to be defined at this step of the design. These are the structure of the models and the value of theirs parameters. The first topic is related to the feature selection of the pattern recognition field. Depending on the task, different features based on the lognormal modeling can be considered: the lognormal parameter themselves, their central tendency, their dispersion, the fitting accuracy (SNR), the number of lognormal components necessary to model a complex motion, etc. A limited number of features (about 5 to 20) are considered, depending on the neuromuscular task analyzed. Main effects and interactions can be considered but as the number of possible interactions is generally pretty large, it seems best to consider only the main effects and the interactions that can be justified from a theoretical perspective. Keeping the number of variables considered as low as possible in the model building process helps avoid an over fitting (i.e. the larger the number of feature tested, the more probable some of them will be discriminative on the training set only by chance) of the test data which would poorly generalize to the targeted population.

Depending on the number of features considered, the search for the optimal model structure can be more or less exhaustive. A tradeoff that has been proved adequate in our application is to proceed with exhaustive search for all models using one parameter and then for all models using two parameters. If the best model (evaluated as the one maximizing the area under the ROC curve) is obtained with only one parameter, then the search is terminated. Else, all three-parameter models are tested. If the best model is obtained with only two parameters, then the search continues. Else, the search continues following the same pattern. Exhaustive search with more than three parameters start to be quite time consuming. Therefore, the first parameter of the four-parameter models can be selected as being the first parameter of the best three-parameter model. Then, an exhaustive search is performed to find the best three supplementary parameters which give the best result. For the five-parameter models, the two first parameters are fixed as those of the best four-parameter model, and so on.

The second topic concerns the determination of the values of the model parameters. This is a simple matter using any statistical software (e.g. R) when the structure of the model is established.

All these design steps are to be performed on a training data set. In our case, to test stroke susceptibility, we used a training set of 120 subjects which has already been described in length elsewhere [3]. This sample encompasses subjects of both genders, with age varying from 25 to 85 years old. Subjects who are healthy, at risk of brain stroke, or who have suffered from a brain stroke are included in this sample. The presence of six of the most important brain stroke risk factors has been recorded for each subject. These factors are cigarette smoking (SM), obesity (OB), hypertension (HT), hypercholesterolemia (HC), diabetes mellitus (DM), and cardiac problems (CP).

3.3.2 Statistical model application

This process is really what is represented as the step 3 in fig. 1 since it is actually the process that is taking place when the system is used by a final user. Its implementation is relatively simple using any modern statistical software. This process takes the values of the selected features for the patient to diagnose and put them in the model previously built to compute a probability of class membership ($P_m$). For example, $P_m = 0$ means that we are sure that the subject does not have the disease and

3.4. Decision making

The decision making process is depending on the cost associated with the number of both the false positive (FP) and the false negative (FN) diagnostics. A decision threshold ($\lambda$) must be found such that it optimizes the following problem:

$$\min_{\lambda} C_{FP}FP(\lambda) + C_{FN}FN(\lambda)$$

(8)

where $C_{FP}$ and $C_{FN}$ are the cost associated to the false positive and the false negative diagnostics, respectively. The choice of a value for these costs is not related to engineering but to medical system management so we will not venture in proposing a value for them. However, once these costs have been defined, $FP(\lambda)$ and $FN(\lambda)$ can be computed for a range of values $\lambda$. Obtaining the optimal value ($\lambda^*$) is then trivial. Next, the diagnostic for a new subject can be made according to a rule like the following: the subject is diagnosed as having the disease if $P_m > \lambda^*$, else the diagnostic is negative.

4. SYSTEM PERFORMANCE EVALUATION

The global behavior of the system is best studied with receiver operating characteristic (ROC) curve analysis [30] which allows to see the operating accuracy of the system for various decision thresholds. Ideally, these evaluations should be performed on a different dataset than the training one (i.e. the one used to choose the structure and the parameter values of the statistical models). This helps to avoid inaccurate results due to potential modeling artifacts or methodological bias and increases the odds of obtaining a good external validity (i.e. getting results that are not only good on the training set but on the whole population of interest).

However, in practice, data collection can be very expensive and cross-validation might be considered. In our case, we used a “leave-one-out” cross-validation. In this technique, one sample is left out to compute the model parameters and, then, the probability of class membership is evaluated on the built model for this left out sample. This procedure is repeated such that all the samples are left out once. The class membership probabilities can then be used to compute the ROC curve and the area under the curve (AUC). This statistics correspond to the probability $P(P_{mp} > P_{mn})$ where $P_{mp}$ and $P_{mn}$ are, respectively, the membership probabilities for a samples coming from a subject having or not the studied disease. Hence, AUC should equals 0.5 for a completely random classifier and 1.0 for a classifier making perfect diagnostics.

5. RESULTS

The results of our efforts have been tested for the brain stroke risk factor predictability as a first step toward the brain stroke risk assessment based on human motion analysis. To that end, we have tested the predictability of the six risk factors previously enumerated. Some of the results have already been published in a more extended form [3] but the complete summary of our results is under preparation as a Ph.D. thesis [17]. To get an appreciation of the results, we summarize in table 1 the best AUC obtained so far for three tasks of the Sign@mèdic project.

<table>
<thead>
<tr>
<th>Risk factors</th>
<th>Speed-accuracy tradeoffs</th>
<th>Triangular drawings</th>
<th>Maximal frequency oscillations</th>
</tr>
</thead>
<tbody>
<tr>
<td>DM</td>
<td>0.848</td>
<td>0.820</td>
<td>0.759</td>
</tr>
<tr>
<td>HT</td>
<td>0.739</td>
<td>0.801</td>
<td>0.766</td>
</tr>
<tr>
<td>HC</td>
<td>0.751</td>
<td>0.732</td>
<td>0.661</td>
</tr>
<tr>
<td>CS</td>
<td>0.711</td>
<td>0.700</td>
<td>0.600</td>
</tr>
<tr>
<td>CP</td>
<td>0.801</td>
<td>0.811</td>
<td>0.735</td>
</tr>
<tr>
<td>OB</td>
<td>0.725</td>
<td>0.681</td>
<td>0.753</td>
</tr>
</tbody>
</table>

As can be seen, the AUC range between 0.60 and 0.85. These AUC are indicative of a certain predictability of brain stroke risk factors based on human movements. They should not be taken only for themselves (simple diagnostic tools with AUC close to 1.0 exist for some of these factors, such as a questionnaire for smoking) but as evidence of links between the motor control and the brain stroke susceptibility. Longitudinal data will be necessary to obtain more accurate and detailed portrait of these relationships so as to know if stroke susceptibility can be assessed by the means of movement analysis in conjunction with the traditional risk factors evaluation.

Some conditions seem to be differentially diagnosed using different tasks. For example, the presence of cardiac problems is best diagnosed using more complex tasks like triangle drawings while the worst prediction is obtained using maximal frequency oscillations. The opposite conclusion stands for obesity, which can be better identified using oscillatory motions. Although such conclusions are not yet statistically supported (i.e. no test has been ran to assess the statistical significance of these differences since it is not obvious how these test could be formulated), these preliminary results are exciting as they suggest that specific risk factors may have distinct effects on the motor control. This conclusion will of course have to be corroborated by further researches.

6. CONCLUSION

In this communication, we have presented the result of our efforts concerning the design of a diagnostic system for neuromuscular disorders using only the kinematic of human movements. Such an approach is interesting as it is not invasive, it can be implemented using low cost hardware, and it can run on a standard laptop. We have described the decision made at all levels of the design process, from the data acquisition down to the system...
performance evaluation. Some typical results have also been given concerning the assessment of brain stroke susceptibility. There is still a lot of research to make to identify the most discriminant features and the way to use them to exploit movement kinematic information to assess the presence of health problems such as brain stroke or neuromuscular disorders. However, this work demonstrates the feasibility of this approach in hope of drawing more attention on this innovative topic.

Possible future works include the combination of the classifiers used for the different neuromuscular tasks in a common diagnostic system to take benefit of the possible complementarity of the tests used in our experiment.

REFERENCES


