Handwriting and Speech Prototypes of Parkinson Patients: Belief Network Approach

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Abstract

Articulator phonetics and handwriting dysfunctions are frequent observations in Parkinson's disease (PD). In this paper we make an inductive study of speech and handwriting skills of PD patients by proposing ways for discovering prototypes of PD patients. Each discovered prototype consists of labeled cluster that combines a similar handwriting and speech skills. For this approach, a mixed acquisition system of electronic pen and speech signals have been performed through voice and handwriting experiments on ten PD patients that share the same experimental conditions. The acquired signals were preprocessed and subjected to feature extractor. Our modeling approach is based on unsupervised learning of a probabilistic graphical model, i.e. a Bayesian Belief Network (BBN) based on Expectation Maximization (EM) algorithm. The structure components of BBN consist of layered architecture and hidden variables hierarchy. Each written and spoken test is represented by its own local hidden pattern; we considered that there exists a global hidden pattern dealing with each local pattern. The discovered patterns have been labeled and then conceptualized as a prototype to serve as a helpful assistant to a motor diagnostic tool based on articulator and handwriting diagnosis, more specifically for PD.

Keywords: *Axial Symptoms, Bayesian belief Network, Classification, Clustering, Data mining, EM Algorithm, Hidden Variables, Hierarchal structure, Neuroscience, Parkinson disease (PD).*

1. Introduction

Handwriting is a very active area of research which brings together psycholinguists, psychologists, specialists in motor control and artificial intelligence. It is a complex skill that depends on the maturation and integration of cognitive ability, perceptual, psychometrical, and motor control [1, 2, 3]. Also, "speaking" as a basic mode of communication, is the most complex motor skill humans can perform. Disorders of speech and language are the most common squeal of brain disease or injury [4]. PD is a disorder of the central nervous system that has an effect on controlling muscles, thus it influences movement, speech and handwriting of patients [5]. The handwriting of Parkinson Disease Patient (PDP) is often characterized by micrographia (reduction of letter size during continuous writing [6]). It has also been reported that kinematic features (e.g. speed, acceleration, and stroke duration) of handwriting movements are affected by PD [6,7,8,9]. Researchers estimate that 89% of people with PD have speech and voice disorders including disorders of laryngeal, respiratory and articulatory function [10]. Moreover, the parkinsonian speech is characterized by reduced vocal loudness, monotone, breathy or hoarse voice, and imprecise hypokinetic [11]. Model disturbances of speech, gait and balance in PDP are considered to be some of the most disabling axial symptoms [12]. Recent research reports have suggested that modulation of the activity of an area in the brainstem, the Pedunculopontine nucleus (PPN)[1] is beneficial in the treatment of axial symptoms [13], furthermore (PPN) is a brain stem locomotive center which is involved in the processing of sensory and behavioral information [14]. Handwriting and Speech Skills (HSS) of PD patients can behave as axial symptoms thus it has been assumed in this paper that PPN influences these symptoms. Therefore PPN was represented by a hidden variable in the framework of Belief Bayesian Network (BBN) formalism. The hidden variable is evaluated according to handwriting and speech measured features that are collected from PDP via a particular experimental protocol. Our aim is to identify patterns, by clustering (PDP) according to their HSS. The discovered PDP clusters represent a coherent unity more easily identifiable and more informative at the level of writing and acoustic features. These can serve as a fundamental reference for future critical assistance, such as a motor diagnostic tool based on speech and handwriting skills of PDP.

The first part of this article discusses the experimental and data acquisition system utilized. The second part gives a clear explanation of the modeling approach, whereas the obtained results are described and illustrated in the third and fourth part as a local and global prototype. Finally the last part holds the general conclusion that is accomplished.

[1] The pedunculopontine nucleus has been highlighted as a target for deep brain stimulation for the treatment of freezing of postural instability and gait disorders in Parkinson's disease and Progressive Supranuclear Palsy [11].

2. Experiments

Ten subjects diagnosed with PD (eight males and two females) were recruited, without evidence of other forms of Parkinsonism. Handwriting and speech data were collected separately from each patient in the PD expert's clinic. Most Patients did not perform any voice therapy for at least one month prior to data acquisition. None of the patients had performed surgical implementation of deep brain stimulation (DBS) [2] . The extracted handwriting and acoustic features from each patient were used later in the clustering and modeling for the BN formalism.

2.1. Handwriting and Speech Platform

2.1.1. Handwriting

For measuring the kinematic features of PD; several traces were proposed by an expert in the field of neurology. Each patient was asked to write four traces; next we will specify the experimental protocol, conditions, traces and extracted features.
Trace L: An axiomatic trace that must be written fifteen times in a cursive pattern (Figure 1); which requires repetition of a counter clockwise loop progression to the right. The patient must try to write the whole trace with one stroke.
Trace Eight (8): This trace obliges patients to make a counter active movement that makes writing this axiomatic trace more complex than trace L. It must be written ten times horizontally. The patient must trace each character spaced out such that characters must not be connected.
Trace Infinity (∞): It must be written ten times vertically. It is similar to trace eight, but it shows higher level of complexity due to the presence of mental rotation imposed by the patient while writing.
Trace Phrase: The phrase is "the killing bullet is fast" (Figure 1). The patient is being asked to write this phrase five times in a cursive pattern. The fifth is the one that was used for the survey. Hence this test is considered as a kind of hand motor physiotherapy.

Fig. 1 Proposed traces example.

The equipments used in the acquisition of the handwriting data are the digitizer tablet (Wacom Intuos2), a notebook computer and developed graphical interface software that records online all the raw data supplied by the digitizer for each trace done by the patient.
The extracted kinematic parameters that fit to the characteristics of different handwriting traces are:
Mean velocity: The mean of instantaneous velocities of the patient's trace during the test.
Fluidity: The average number of inversions in velocity peak per stroke. This feature represents the movement fluency of the patient during the test.
Number of strokes: The number of times the patient writes a complete mark across the tablet, (i.e. the number of times the pen is removed and placed over the tablet).
Duration of pause in context: The average duration of each pause in context done by the patient.
Mean pressure: is the mean pressure exerted by the patient on the tablet during the test.

2.1.2. Speech

Concerning the voice of PDP, many articles indicated a voice tremor, poor vocal fold closure and reduced amplitude. Asymmetry or slow vibratory patterns of the vocal folds [16, 17], [18] specify a reduced range of vowel articulation. In our experiments acoustic feature measurements of PDP were done by quantifying several vocal phonations. Each patient was asked to emit a sustained vowel "a" and a short sentence in Arabic. The use of sustained vowel phonations was to assess the degree of vocal symptoms in the acquired voice. The patients were requested to hold steady the frequency of phonation for as long as possible. They were tested individually in a quiet room, the patient being asked to emit the required vowel and sentence. The captured vowel was repeated five times, the fifth signal was analyzed, while the phrase was repeated three times, the third was analyzed. The repeatability of the signals is for the fact that the person shows symptoms of fatigue after repetition and the parameter will be more observable.
The equipments used for extracting the speech features are: a high-quality *noise-canceling* microphone headset for recording patient voice signals designed to filter out ambient noise from the desired sound and a notebook computer. We applied the Praat software package which has been widely and recently used [19,20] as speech features extractor, and specifically as a PD speech diagnostic. Features extracted from the vowel included the maximum phonation time (MPT), frequency perturbation (jitter), intensity perturbation (shimmer), and harmonic/noise Ratio (HNR). While the standard deviation (STD intensity) of the intensity and the voice breaks were extracted from the phrase.

3. Modeling approach

Currently, attractive requests of graphical models, particularly in the form of BBN classifiers, can be found in many disciplines, such as: finance (risk evaluation

[2] One of the most important solutions proposed to reduce the effect of the PD symptoms is the DBS surgery; this adjustable, reversible therapy uses an implanted device (near the collar bone) that electrically stimulates areas of the brain. It enables the brain circuits that control movement to function better [15]

and stress test) [21, 22], network diagnosis [23], and for medical applications [24, 25, 26].
BBNs are high-level representation of probability distributions over a set of variables that are used for building a model of the problem domain. It provides a compact and natural representation, an effective inference, and efficient learning [27, 28]. Based on BBN framework models, more specifically the Hierarchical Latent Class (HLC) models anticipated [29, 30, 31] and used [2, 32, 33], we model our problem with HLC. Those are a tree-structured Bayesian Networks (BNs) where leaf nodes are observed while internal nodes are hidden. We represented the physiological brain structure (i.e. PPN) by a hidden variable that influences both handwriting and speech measuring variables. Continuous variables have been discretized based on Akaike's criterion [34].

3.1. Clustering

The fundamental hypothesis published in [3, 33, 35] assume that if features of writing (or speech) of a set of PD pupils are similar with respect to a given metric, then these pupils nearly share the same handwriting (or speech) Pattern. Part of our work, therefore, aims at identifying and studying patterns by clustering[3] (PDP) according to their HSS. Thus, the discovered PD clusters can serve as a fundamental reference for future helpful assistance, such as a motor diagnostic tool based on HSS of PD. For this reason we use one of the partitioning methods in which the clusters are used to optimize an objective partitioning criterion. More specifically we use the EM algorithm which is a broadly applicable approach to the iterative computation of maximum likelihood (ML) estimates, useful in a variety of incomplete-data problems [36, 37]. Typically, the bottom layer is the visible layer, containing the observable data variables, and the higher layer is the hidden layer, representing latent variables.

3.2. Belief Network Components

There are none well justified theoretical selection criteria for HLC models in particular and BNs with latent nodes [30, 38]. The challenge is that both the BN structure and the number of clusters are partially dependant on the neurologist expert knowledge, and the parameters (i.e conditional probabilities between children and their parents) are estimated by EM algorithm. The missing data in this challenge are hidden variables treated as a new unlabeled pattern in the outline of unsupervised learning (i.e. clustering). Five local Bayesian naïve and non-naïve structures were implemented. Which are, speech structure, trace L structure, trace Eight structure, trace Infinity structure and trace Phrase structure. The high number of local structure leads us to consider the clusters number as two for each local structure. After clustering, we attempted to split the feature values into a set of nominal values based on a percentage scale. This methodology lead to more informative results interpretation for each discovered cluster [33, 39]. Thus, using the below scale (Figure 2) each feature value was categorized according to five levels.

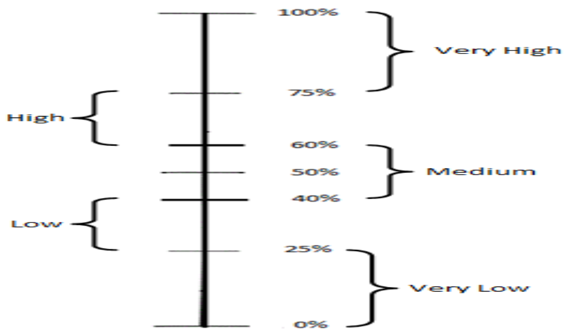

Fig. 2 Percentage scale.

4. Local Prototypes

4.1. Voice Local Structure

The optimal choice for voice structure consists of four features: Jitter, HNR, MPT, and STD intensity. Where Shimmer and voice breaks were excluded (Figure 3). The clustering result and the common characteristics of each cluster for the voice local structure are summarized in Figure 4.

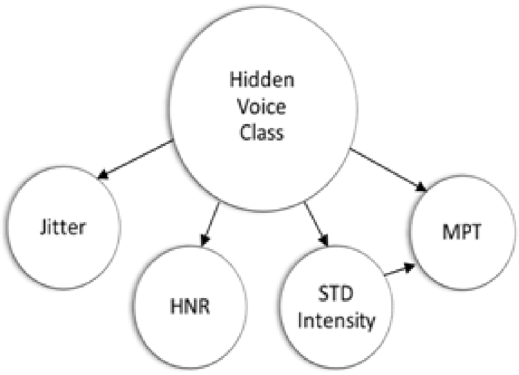

Fig. 3 Voice local structure.

The expert indicated that patients in C1 have more voice strength than in C2, since their MPT is longer. Moreover, patients in C1 have less amplitude perturbation (jitter) than in C2. This implies that patients in C1 have more voice stability. In addition, patients in C1 have higher HNR, thus lower degree of hoarseness. Finally, from our point of view, patients that have high or low STD intensity are able to control their voice levels better than in C2 that have medium STD intensity.

[3] Clustering is the process of grouping the data into classes or clusters, so that objects within a cluster have high similarity in comparison to one another [37].

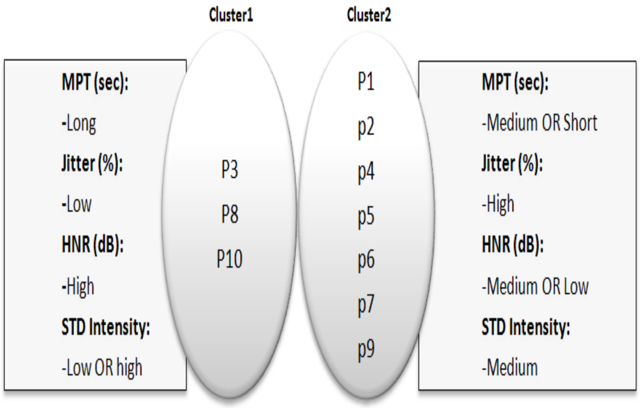

Fig. 4 Clustering result and feature characteristics of voice clusters.

According to this clustering, and based on the above interpretation, we can say that patients in C1 compared to C2 have better physiological parameters. Under expert guidance, patients' information were reviewed, it has been noticed that patients in C1 are all involved in the teaching domain, which means they perform voice activities as a part of their daily life, as if they are practicing speech therapy. Hence, our voice classification is dependent on the improvement of the physiological trends based on the extent to which the patient practices his voice in the daily life.

4.2. Trace Phrase Local Structure

The optimal choice of structure for trace phrase is a naïve one Figure 5 that integrates all five features: velocity, pause-in duration, fluidity, number of strokes and mean pressure.

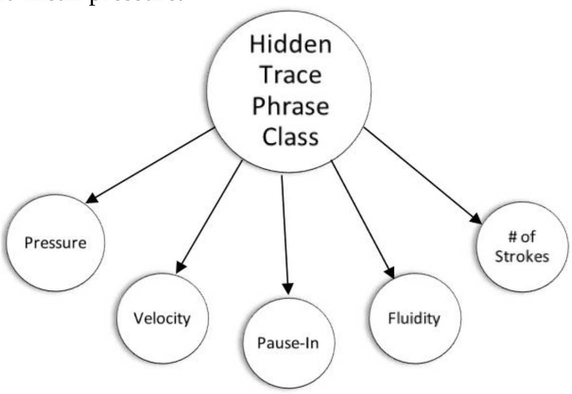

Fig. 5 Trace Phrase Structure

After presenting the classification results as shown in Figure 6, we can observe that patients in C1 who have moderate kinematic parameters have better handwriting abilities with respect to patients in C2 that have extreme kinematic parameters. We draw attention to the fact that the acquisition of trace phrase was itself a kind of ***hand-motor physiotherapy*** for the patients. Thus we can say that C1 positively responded to the hand-motor physiotherapy, while C2 negatively responded to this kind of physiotherapy.

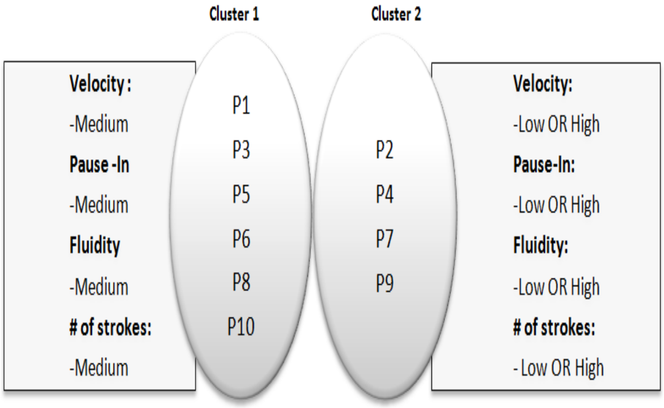

Fig. 6 Clustering result and feature characteristics of trace infinity clusters.

From this result, we can state that this kind of physiotherapy was an effective treatment approach for addressing kinematic parameters. The analysis of kinematic aspects of trace phrase classified patients who were able to preserve moderate values upon writing this trace.

Furthermore, compared to previous results, we can prove that clinical physiotherapy is more effective than that done at home because patients will take it seriously and try to make control on their handwriting which in turn reveals the kinematic parameters of each patient.

5. Global Prototype

On the way to build our HLC model we considered the obtained handwriting and speech patterns (local prototypes) as leaf nodes for a new Latent Class which is a source influencing and acting on both types of patterns (pattern of speech and writing). Each local prototype has its own particular motor abilities that are represented by hidden discrete variables. This model is conceptualized as a global prototype which deals with each local prototype. The goal of such global prototypes is to model the relation between the PPN (represented as the Global latent class) and the motor abilities of PD patients (represented by the Local latent class). The only assumption we make is that these abilities are independent but conditionally dependent on a hidden global class which is the missing data in this case. For this reason, we used the EM algorithm for calculating the conditional probabilities between local classes and the global class, knowing that the previously calculated conditional probabilities between features (handwriting or speech) and their corresponding class was predetermined for the global model.

After the modeling and learning phase, the global BNs were used as an inference tool. It is attainable to compute and display the conditional probability distribution of any variable given the observation of any other variables.

For instance through inference, we can make different tradeoffs between traces and voice parameters: what is the probability that a parkinsonian has such a difficulty in handwriting, knowing that this parkinsonian has such a fixed pattern of speech.

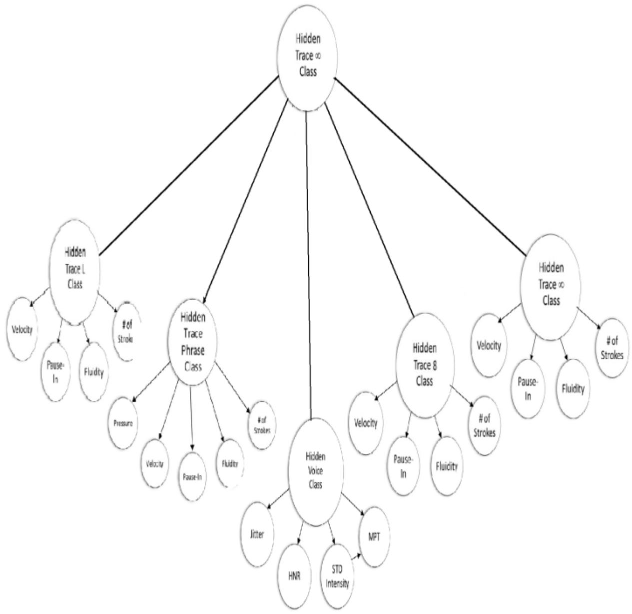

Fig. 7 Global structure.

5.1. Interpretation

Our approach had resulted in three groups' classification as shown in Figure 8.

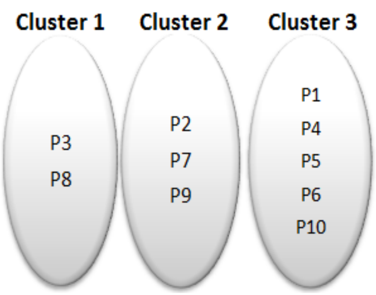

Fig. 8 Clustering results for the Global Structure.

In Table 1 the common feature characteristics of each cluster are summarized, where each feature was characterized according to resulting output measurements in the form of low (L) , high (H) , and medium (M).

After tabulating these groups, it was recognized that C1 include two patients (P3 and P8), that have been clustered together in all local prototypes. According to these local prototypes interpretations, C1 are patients having better acoustic features. On the other hand patients were capable of controlling all the writing abilities while writing each trace test (axiomatic or non-axiomatic). Also they positively responded to the hand motor physiotherapy (Trace Phrase). Thus, we can conclude that patients in C1 are capable of controlling voice and handwriting motor abilities probably due to the fact that they are in the early stages of disease duration (3-4 years). As for C2 Patients, they were clustered together in three local prototypes (voice, trace L and phrase). These local prototypes interpretations indicate that C2 patients have low voice quality with respect to the extracted acoustic features. On the other hand they showed weak ability to control axiomatic traces (Trace L). Also they negatively responded to hand-motor physiotherapy (Trace Phrase). Hence, C2 patients weren't able to control their handwriting or acoustic abilities. This is maybe linked to their belated disease duration (11-15 years). Finally, the common feature characteristics of C3 patients are moderate kinematic features during hand-motor physiotherapy (trace phrase) and moderate acoustic features acquired from the sustained vowel. In addition we noticed that C3 patients have disease duration (2-6 years). No further interpretation for C3 patients was required. We suppose that this cluster should be divided into sub-clusters for labeling intentions.

Table 1 : Common feature characteristics of global structure clusters.

	Trace LL	***Trace 8***	***Trace ∞***	***Trace Phrase***	***Voice***	
Cluster 1						
Velocity	M	L	L	M	MPT	H
Pause-In	>Zero	H	H	M	Jitter	L
Fluidity	H	L	L	M	HNR	H
# of Strokes	>One	L	H	M	STD Intensity	H
Pressure				M		
Cluster 2						
Velocity					MPT	M
Pause-In	Zero				Jitter	M
Fluidity	V.H			H	HNR	
# of Strokes	One	L	L		STD Intensity	
Cluster 3						
Velocity	M	H		M	MPT	M
Pause-In				M	Jitter	M
Fluidity				M	HNR	M
# of Strokes				M	STD Intensity	
Pressure				M		

6. Conclusion

We have described a way for labeling *Handwriting and Acoustic Prototypes* of PD patients. Based on BBN formalism combined with a Bayesian clustering algorithm (i.e EM Algorithm) that integrates a *priori* knowledge provided by experts. More specifically we used HLC models which are tree-structured BNs where leaf nodes are observed while internal nodes are hidden.

We represented the physiological brain structure (i.e. PPN) by a hidden variable that influences both handwriting and speech measuring variables.
In this paper we use an objective contribution to evaluate the performance follow up of PDP with regarding their HSS. The results of our research should therefore appeal to neurologists and doctors who are interested in the PDP development of axial symptoms. We infer the obtained model by showing proper conditional probabilities, for example, ***what is the probability that Parkinsonian has such difficulty in writing in advance to knowing such a fixed pattern of speech.***
In the clustering and modeling approach, our contribution highlights groups of patients who share the same prototypes of acoustic and handwriting features. Through a comparative analysis of the obtained clusters, we have shown that each group of patients constitutes a coherent unity, more easily identifiable and more informative at the level of handwriting and acoustic features. From a cognitive point of view, the behavior of a group could be the function of a specific central representation. Therefore the patients grouped together in the same cluster could share common expertise at the motor program level.
In the local approach, the results of our voice local model, classified patients according to their ability to ***control*** their voice, which is related to which extent they utilize their voice in their daily activity. Whereas the results of the handwriting local models showed that traces L, Eight and Infinity clustered patients according to their ability of controlling the handwriting of each trace. Moreover trace phrase, clustered patients with respect to their response ability to hand-motor physiotherapy. The result obtained from this trace, reveals that clinical physiotherapy leads to effective improvements for PD patients' ***motor abilities*** more than it done at home.
As for the results of the global model, three clusters were obtained. C1 is capable of controlling voice and handwriting motor abilities; C2 wasn't able to make any control whether on handwriting or acoustic abilities; C3 is not yet labeled.

References

[1] I. Sage, and P. Zesiger, " Profils de scripteurs âgés de 8 à 12 ans ", L'écriture et ses pratiques du 8 au 10 Novembre 2010 - Université de Poitiers, 2010 .
[2] I. Zaarour, B. El-Eter, P. Leray, L. Heutte, J. Labiche, D. Mellier, and M. Zoater. "Une modélisation de haut niveau des stratégies d'écriture motrice d'enfants en scolarité primaire : approche bayésienne", Journal de Physique IV, Vol 124, 2005, pp. 230-236.
[3] I. Zaarour, P. Leray, L. Heutte, B. Eter, J. Labiche, D. Mellier, and M. Zoaeter. "Modelling of handwriting prototypes in graphonomics : Bayesian network approach", 5th EUROSIM Congress on Modelling and Simulation, EUROSIM'04, Marne-la-Vallée, France, 2004, pp. 78 (Proceedings on CD-ROM).
[4] B. Maassen, and P. van Lieshout, "Speech Motor Control New developments in basic and applied research", ISBN 3: 9780199235797ISBN10 , Wouter Hulstijn (Editor) ,2007.
[5] R. Pahwa, K. Lyons, and W. Koller, "Handbook of Parkinson's Disease: Neurological Disease & Therapy", Informa Healthcare USA, Inc, 4th ed., New York 2007
[6] H. Teulings, and G. Stelmach, "Control of stroke size, peak acceleration, and stroke duration in parkinsonian handwriting", Human Movement Science,Vol. 10, Issue: 2-3, 1991, pp. 315-334
[7] O. Tucha, L. Mecklinger, J. Thome, A. Reiter, G. L. Alders, H. Sartor, M. Naumann, and K. Lange, "Kinematic analysis of dopaminergic effects on skilled handwriting movements in Parkinson's disease", J Neural Transm, Vol. 113, 2006, pp. 609–623.
[8] T. Flash, R. Inzelberg, E. Schechtman, and A. Korsczyn, "Kinematic analysis of upper limb trajectories in Parkinson's disease", Exp Neurol, Vol. 118, 1997, pp. 215–226.
[9] M. Longstaff, P. Mahant, M. Stacy, A. Van Gemmert, B. Leis, and G. Stelmach, "Continuously scaling a continuous movement: Parkinsonian patients choose a smaller scaling ratio and produce more variable movements compared to elderly controls", in RGJ Meulenbroek & B Steenbergen (eds), Proceedings of the 10th Biennial Conference of the International Graphonomics Society, Nijmegen, The Netherlands, International Graphonomics Society, Nijmegen, pp. 84-89.
[10] L.O. Ramig, C. Fox, and S. Sapir, "Speech treatment for Parkinson's disease", Expert Rev, Neurotherapeutics Vol. 8, No. 2, 2008, pp. 299-311.
[11] S. Factor, and W. Weiner, "Parkinson's disease: diagnosis and clinical management", Demos Medical Publishing, LLC, 2nd ed, New York 2008.
[12] D. Muslimovic, B. Post, J. Speelman, B. Schmand, and R. De Haan, "Determinants of disability and quality of life in mild to moderate Parkinson disease", In Neurology, Vol. 70, Issue: 10, 2005, pp. 2241-2247
[13] P. Mazzone, A. Lozano, P. Stanzione, S. Galati, E. Scarnati, A. Peppe, and A. Stefani "Implantation of human pedunculopontine nucleus: A safe and clinically relevant target in Parkinson's disease", in Neuroreport, Vol. 16, No. 17, 2005, pp. 1877-81.
[14] C. Hamani, E. Moro, and A. Lozano, "The pedunculopontine nucleus as a target for deep brain stimulation", in Journal of Neural Transmission, Vol. 118, No. 10, 2010, pp. 1461-8
[15] HR. Siebner, and A. Ceballos-Baumann, "Changes in Handwriting Resulting From Bilateral High-Frequency Stimulation of the Subthalamic Nucleus in Parkinson's Disease", Journal of Movement

Disorders, Name, Vol. 14, No. 6, 1999, pp. 964–971.

[16] K. Perez, LO. Ramig, M. Smith, and C. Dromey, "The Parkinson larynx: tremor and videostroboscopic findings", J. Voice Vol. 10, No. X, 1996, pp. 354-361.

[17] M. Smith, LO. Ramig, C. Dromey, K. Perez, and R. Samandari, "Intensive voice treatment in Parkinson's disease: laryngostroboscopic findings ", J. Voice Vol. 9, No. X, 1995, pp. 453-459.

[18] S. Sapir, J. Spielman, L. Ramig, B. Story, and C. Fox, "Effects of intensive voice treatment on vowel articulation in dysarthric individuals with idiopathic Parkinson's disease: acoustic and perceptual findings", J. Speech Lang. Hear. Res. Vol. 50, No. X, 2007, pp 899-912.

[19] J. Rusz , R. Cmejla , H. Ruzickova, and E. Ruzicka, "Quantitative acoustic measurements for characterization of speech and voice disorders in early untreated Parkinson's disease", Journal of Acoustical Society of America, Vol. 129, No. 1, 2011, pp 350-367.

[20] MA. Little, PE. McSharry, EJ. Hunter, J. Spielman, LO. Ramig , "Suitability of dysphonia measurements for telemonitoring of Parkinson's disease", IEEE Trans Biomed Eng, Vol. 56, No. 4, 2009, pp 1015-1020.

[21] R. Rebonato, "A Bayesian approach to stress testing and scenario analysis", Journal of Investment Management, Third Quarter, 2010.

[22] A. Meucci, "Fully Flexible Views: Theory and Practice ", Risk, Vol. 21, No. 10, 2008, pp. 97-102.

[23]R.M. Khanafar, B. Solana, J. Triola, R. Barco, L. Moltsen, Z. Altman, and P. Lazaro, "Automated Diagnosis for UMTS Networks Using a Bayesian Network Approach", IEEE Trans. on Vehicular Technology, Vol. 57, No. 4, 2008, pp. 2451-2461.

[24] R. Intan and O. Y. Yuliana, "Fuzzy Bayesian Belief Network for Analyzing Medical Track Record", Journal of Advances in Intelligent Information and Database Systems, Studies in Computational Intelligence, Vol. 283, 2011, pp. 279-290.

[25] J.P. Sacha, L. Goodenday and k. J. Cios, "Bayesian learning for cardiac SPECT image interpretation", Journal of Artif Intell Medline, Vol. 26, No. 1-2, 2002, pp. 109-143.

[26] Y. B. Gong, N. L. Zhang, and S. H. Gao, "A study of symptom distribution regularities of Type II Diabetes using latent structure models", Journal of World Science and Technology-Modernization of Traditional Chinese Medicine and Materia Materia, Vol. 4, No. 4, 2009, pp. 516-521.

[27] N. Friedman, "Learning Bayesian networks in the presence of missing values and hidden variables", in D. Fisher (Ed.), Proceedings of the Fourteenth International Conference on Machine Learning, San Francisco, Calif. Morgan Kaufmann, 1997.

[28] C. Borgelt, M. Steinbrecher and R. Krus, "Graphical Models: Representations for Learning, Reasoning and Data Mining", United Kingdom: John Wiley & Sons, Ltd, 2009, ISBN: 978-0-470-72210-7

[29] N.L. Zhang, and T. Kocka, "Efficient learning of hierarchical latent class models, Tools with Artificial Intelligence", in 16th IEEE International Conference, Journal of Machine Learning Research Vol. 5, No.5 , pp. 697-723.

[30] Y. Wang, and N.L. Zhang, "Latent Tree Models and Approximate Inference in Bayesian Networks ", Journal of Artificial Intelligence Research, Vol. 32 No. 21, 2008, pp. 879-900

[31] N.L. Zhang, "Hierarchical Latent Class Models for Cluster Analysis", Journal of Machine Learning Research, Vol. 5, No. 1, 2004, pp. 697-7232004

[32] I. Zaarour, L. Heutte, P. Leray, J. Labiche, B. Eter, and D. Mellier, " Clustering And Bayesian Network Approaches For Discovering Handwriting Strategies Of Primary School Children", International Journal of Pattern Recognition and Artificial Intelligence, Vol. 18, No. 7, 2004, pp. 1233-1251.

[33] I.Zaarour, J. Labiche, and D. Meillier, "Classification de l`Écriture des Groupes d`Enfants Typiques", in 3rd International Conference: E-Medical Systems, 2010, Vol. 24, pp. 12-14.

[34] D. Song, C. E. Henrik, K. Huebner, and D. Kragic, "Multivariate Discretization for Bayesian Network structure learning in robot grasping", in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2011, Vol. 11. pp. 20-27.

[35] I. Zaarour, L. Heutte, B. El-Eter, J. Labiche, D. Mellier, P. Leray, and M. Zoaeter, "A probabilistic modeling of the writing strategies evolution for pupils in primary education", in 11th Conference of the International Graphonomics Society, 2003, Scottsdale, Arizona, Vol. 3885, pp. 174-177.

[36] G. J. McLachlan and S.K. Ng , "The Top Ten algorithm in Data Mining", Edited by W. Xindong and V. Kumar , New York: CRC Press Taylor & Francis Group, 2009, ISBN 978-1-4200-8964-6.

[37] J. Han. Friedman, "Data Mining: Concepts and Techniques", Second Edition, ELSEVIER, Morgan Kaufman Publishers.

[38] N. L. Zhang and T. Kocka, "Effective dimensions of hierarchical latent class models", Journal of Artificial Intelligence Research, Vol. 21, No. 1, 2004, pp. 1-17.

[39] P. Naim, P. Henry, P. Leray, O. Pourret, and A. Becker, "Réseaux bayésiens", Groupe Eyrolles, 2008, ISBN : 978-2-212-11972-5.