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Automated classification of neurological disorders of gait using spatio-temporal gait parameters

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ABSTRACT

Objective: Automated pattern recognition systems have been used for accurate identification of neurological conditions as well as the evaluation of the treatment outcomes. This study aims to determine the accuracy of diagnoses of (oto-)neurological gait disorders using different types of automated pattern recognition techniques.
Methods: Clinically confirmed cases of phobic postural vertigo ($N = 30$), cerebellar ataxia ($N = 30$), progressive supranuclear palsy ($N = 30$), bilateral vestibulopathy ($N = 30$), as well as healthy subjects ($N = 30$) were recruited for the study. 8 measurements with 136 variables using a GAITRite® sensor carpet were obtained from each subject. Subjects were randomly divided into two groups (training cases and validation cases). Sensitivity and specificity of k-nearest neighbor (KNN), naive-bayes classifier (NB), artificial neural network (ANN), and support vector machine (SVM) in classifying the validation cases were calculated.
Results: ANN and SVM had the highest overall sensitivity with 90.6% and 92.0% respectively, followed by NB (76.0%) and KNN (73.3%). SVM and ANN showed high false negative rates for bilateral vestibulopathy cases (20.0% and 26.0%); while KNN and NB had high false negative rates for progressive supranuclear palsy cases (76.7% and 40.0%).
Conclusions: Automated pattern recognition systems are able to identify pathological gait patterns and establish clinical diagnosis with good accuracy. SVM and ANN in particular differentiate gait patterns of several distinct oto-neurological disorders of gait with high sensitivity and specificity compared to KNN and NB. Both SVM and ANN appear to be a reliable diagnostic and management tool for disorders of gait.

1. Introduction

Gait disturbances are a common feature in patients with neurological disorders and have an immense impact on the quality of life. Impairment of gait may lead to a decrement in mobility, social independence, and is an important risk factor for falls (Stolze et al., 2004; Sudarsky, 2001). In internal audit suggested that out of 3503 patients seen at the German Center for Vertigo and Balance Disorders (DSGZ) outpatient clinic, a specialized clinic for vertigo and balance disorders, 46% of patients had a chronic disorder with daily symptoms of postural and gait imbalance.

Conventional gait analysis records temporal and spatial characteristics of the gait cycle during normal walking. When complex gait conditions are included in the protocol, e.g. by adding walking conditions with motor or cognitive dual tasks, or walking at different velocities, results can be used to determine an individual's fall risk, quantify disability and allows a prognosis of the course (Verghese et al., 2009, 2010). While conventional gait analysis may provide a quick overview of gait performance, it often fails to distinguish patients with different pathologies. The reasons have been the huge amounts of generated data, which are difficult to interpret, as well as the absence of specific analysis criteria for pathological gait patterns (Thompson, 2007; Sudarsky, 2001). Increased availability of gait mats and treadmills further demands the development and validation of new analytical and classificatory approaches. In view

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of shared commonalities as well as high dimensionality of gait data, researchers have attempted to use automated pattern recognition systems to classify gait. The automated systems not only provide a class label useful for diagnostic purposes, but also enable clinicians to identify and understand important gait variables unique to individual clinical conditions (Chau, 2001). While current pattern recognition procedures cannot replace clinical acumen, it may help strengthen diagnosis in unclear cases as well as screen large databases for research purposes. This certainty can be further improved as the classifiers can accommodate a wide variety of additional quantitative and qualitative clinical and non-clinical data.

The use of artificial neural networks (ANN) and other pattern recognition techniques in medicine has grown enormously in the last decade (Chau, 2001). In the field of posture research they have been used for prediction, diagnosis and prognosis (Hahn and Chou, 2005; Krafczyk et al., 2006; Brandt et al., 2012). ANNs have also successfully been used for prediction in orthopedic problems affecting gait (Barton and Lees, 1997; Holzreiter and Kohle, 1993; Lafuente et al., 1997). Support vector machines (SVMs), k-nearest neighbor classifiers (KNN) and naive-bayes classifier (NB) are other frequently used methods for gait classification (Sudha and Bhavani, 2012; Lu and Zhang, 2007; Wang et al., 2009; Kamruzzaman and Begg, 2006; Manap et al., 2012). More recent studies have applied Hidden Markov Models, SVMs and ANNs in discriminating dynamic plantar pressure, electro-myography and acceleration profiles often in combination with data reduction procedures such as principal component analysis for feature extraction (Wang et al., 2012; Aung et al., 2013; Klucken et al., 2013; Miller et al., 2013; Tang and Sazonov, 2014). Data compression techniques such as PCA and wavelet transform are especially important in the analysis of high dimensional human gait video datasets (Xu et al., 2012).

Until now, gait pattern recognition has been mostly used on kinematic gait data sets on limited number of groups (Barton and Lees, 1997; Lafuente et al., 1997; Holzreiter and Kohle, 1993). However, acquisition of kinematic data is often time and resource consuming, resulting in its low clinical applicability. The objective of this paper was to validate the possibility of using automated pattern recognition procedures on routine clinical spatio-temporal gait data, as a tool to assist clinical diagnosis. Our study for the first time attempts to use and compare automated pattern classification on five clinical groups utilizing temporo-spatial gait data acquired using a pressure carpet which is both easy and quick to use in clinical settings. Our goal was to determine the typical patterns of pathological gait in phobic postural vertigo, cerebellar ataxia, progressive supranuclear palsy and peripheral bilateral vestibulopathy when compared to normal subjects. Owing to the success in classifying postural data we decided to construct the neural network based on a previous study by our lab (Krafczyk et al., 2006; Brandt et al., 2012).

2. Methods

2.1. Recruitment of the participants

Patients were recruited from the German Center for Vertigo and Balance Disorders (DSGZ) outpatient clinic. We identified clinically clear cases for the following pathologies:

1. Cerebellar ataxia: the diagnosis was based on cerebellar symptoms in clinical neurological examination and atrophy of the vermis or hemispheric regions of the cerebellum, identified using MRI or CT scan. Symptoms were present for the duration of at least 3 months. Patients with neuro-otological signs and symptoms (spontaneous nystagmus, pathological head impulse test, caloric vestibular responses), and polyneuropathy were excluded.
2. Phobic postural vertigo: the clinical diagnosis was based on the criteria of Brandt (1996). Additional inclusion criteria were symptom duration of at least 3 months and the presentation of symptoms on the day of testing. Neuro-ophthalmologic examination and caloric responses in these patients were normal and they had no signs of polyneuropathy. Patients had been off psychotropic medication for more than 1 month, and had no history of alcohol abuse.
3. Bilateral vestibulopathy: patients presenting with instability of gait for at least 3 months and complete severe deficit on clinical testing (bilateral pathologic head-impulse test (Halmagyi and Curthoys, 1988) and absent or maximal caloric responses <5 degrees slow-phase velocity during irrigation with water 30/44 °C), and no signs of polyneuropathy.
4. Progressive supranuclear palsy: patients presenting with bradykinesia and rigidity for at least 3 months duration. Patients also had vertical ocular motor dysfunction (saccadic pursuit or gaze palsy). Patients with morphological pathologies of the midbrain or basal ganglia on MRI scans were excluded.
5. Healthy subjects: they were recruited among healthy relatives of patients and staff and through advertisements in newspapers. All subjects were clinically examined and did not show any vestibular, sensorimotor or neurological abnormalities which could affect gait.

All participants gave their written informed consent prior to the gait measurements. The study was approved by the local ethics committee and performed in accordance to the Statement of Helsinki and its later revisions.

2.2. Gait analysis procedures

Gait analysis was performed using a 6.7-m long pressure-sensitive carpet (GAITRite®, CIR System, Havertown; USA) with a sampling rate of 120 Hz, spatial resolution of ±1.27 cm and temporal resolution of ±1 samples. The carpet system provides the single step values, mean values, and standard deviations for different gait parameters. Gait parameters were obtained during preferred walking speed, slow speed and maximally fast speed, as well as during walking with eyes closed at preferred speed, walking with head extension and walking while performing three different dual tasks (verbal fluency, serial subtraction of 7 and carrying a tray). For the slow walking condition, subjects were asked to walk along the carpet naturally, at their slowest possible speed. Trials with pauses, or prolonged stance phases were excluded and repeated. Dual task verbal fluency gait included a nomination task (i.e. names of animals starting with 'B') while walking along the carpet at normal speed. Dual task subtraction was an arithmetic task (i.e. serial subtraction of 7 from 105) while walking along the carpet at normal speed. Task prioritization was achieved by asking the subjects to focus on the non-gait task.

2.3. Data analysis

17 discreet gait variables were analyzed from each subject for each gait modality leading to a total of 136 discreet measurements for each subject. Variables measured included: functional ambulatory profile (FAP) (17), walking velocity (m/s), normalized walking velocity (m/s), step frequency (Hz), support base (m), stride length (m), stride time (s), double support time (s), double support percentage (%), swing and stance percentages (%), coefficient of variation (CV) of stride length, stride time, support base and double support time (standard deviation divided by the mean as a percentage; %), step length and step time differences (difference between left and right foot). The FAP score is the linear relationship of step length to leg length ratio to step time when the velocity is