Aiding Diagnosis of Normal Pressure Hydrocephalus with Enhanced Gait Feature Separability

Shanshan Chen[1], Adam T. Barth[4], Jeffery T. Barth[2], Bradford C. Bennett[3], Maïté Brandt-Pearce[1], Donna K. Broshek[2], Jason R. Freeman[2], Hillary L. Samples[2], John Lach[1]

[1]Charles L. Brown Department of Electrical and Computer Engineering
[2]Department of Psychiatry and Neurobehavioral Sciences
[3]Motion Analysis and Motor Performance Laboratory, Department of Orthopedic Surgery
UVA Center for Wireless Health
University of Virginia, Charlottesville, VA, USA 22904
[4]Wireless Health Interactive, LLC, Vienna, VA, USA 22182
{sc2xh, atb4c, jtb4y, bcb3a, mb9q, dkb6v, jf4z, hls5w, jlach}@virginia.edu

ABSTRACT

Normal Pressure Hydrocephalus (NPH) is a neurological condition that challenges differential diagnosis, as the symptoms – cognitive and gait impairment and urinary incontinence – are similar to those of many aging disorders, including Alzheimer's disease and other forms of dementia. Since NPH is caused by abnormal accumulation of cerebrospinal fluid (CSF) around the brain, a high volume lumbar puncture (HVLP) to remove excess fluid is used as the stimulus for a suspected NPH patient, and a diagnosis is made based on the observed cognitive and functional response.

Gait features have long been used as functional indicators in the pre- and post-HVLP assessment. However, these assessments are limited to visual observation in the clinic. Therefore, only simple gait features such as walking speed (based on time to walk 10m) and average stride length/time (based on the number of steps to walk 10m) are used. However, these features provide limited separability in the NPH diagnosis.

This paper presents methods for enhanced diagnostic separability using additional gait features extracted from an inertial body sensor network (BSN), including stride time variability, double support time, and stability. A pilot study on six HVLP patients – four of whom were ultimately diagnosed with NPH – revealed that gait stability assessed by Lyapunov exponent provides better separability and can enhance the differential diagnosis. In addition, these results suggest that additional testing can be performed continuously outside of the clinic to account for patients' variable HVLP response times.

Categories and Subject Descriptors

J.3 [**Life and Medical Sciences**]: Health, Medical information systems.

General Terms

Measurement, Experimentation, Evaluation.

Keywords

Gait Features; Normal Pressure Hydrocephalus; Diagnosis; Gait Stability; Lyapunov Exponent; Inertial BSN.

1. INTRODUCTION

Normal Pressure Hydrocephalus (NPH) is a neurological condition caused by abnormal accumulation of cerebrospinal fluid (CSF) around the brain [1]. Although NPH can occur in any age, it is normally observed in the aging group. According to recent population-based studies, the prevalence of NPH to be about 0.5% in those over 65 years old, with an incidence of about 5.5 patients per 100,000 of people per year [2] [3]. The symptoms of NPH are usually described as a classic triad of gait disturbance, dementia or mental decline, and urinary incontinence [1], with debilitating effects on patients' and families' quality of life. However, due to the similarities of these symptoms to many aging disorders, such as Alzheimer's disease and other forms of dementia, and individual variability of the symptom expression, the differential diagnosis is challenging. In comparison to other forms of dementia, NPH is reversible after proper medical intervention and may significantly improve patient and caregiver quality of life. If diagnosed successfully as NPH, patients will be treated with an invasive, long term intervention – the ventriculo-peritoneal (VP) cerebral shunt to drain excess CSF to the abdomen where it is absorbed. This shunt surgery does however present great risks, in that it may cause hematoma, cerebral edema, crushed brain tissue and herniation. Therefore, NPH diagnosis accuracy is critical.

To diagnose NPH, a high volume lumbar puncture (HVLP) is performed to remove excess fluid from a suspected NPH patient followed by a clinical evaluation of the cognitive and functional response [1]. Medical literature has suggested that improvement in gait pre- to post-HVLP is often a good functional marker for diagnosis in the decision to proceed with shunt surgery [1]. However, in current clinics, visual observation is still the dominant form of assessment for gait performance; thus, only simple gait features such as walking speed (based on time to walk 10m) and average stride length/time (based on the number of steps to walk 10m) are used. The low resolution and precision of such features do not provide separability in gait performance pre- and post-HVLP. Some clinics have adopted advanced optical motion capture systems for higher precision gait analysis, but that not only requires a dedicated laboratory with expert operation but also involves a cumbersome setup procedure that makes it impractical for use on impaired, fatigued patients who are already undergoing significantly invasive procedures throughout the day [4][5].

Therefore, convenient and accessible yet highly accurate and precise gait analysis tools and methods are needed to enhance NPH diagnosis.

Inertial body sensor networks (BSNs) represent a promising platform for addressing this need. Previous work has demonstrated the potential of using BSNs for assessing gait parameters [6][7][8][9][10]. The rich information provided by 6+ degrees of freedom motion capture systems has enabled many medical studies and clinical applications. However, in order to explore gait features that maximize separability for NPH, as well as other differential diagnoses, several challenges must be overcome. First, gait events need to be accurately detected in order to extract the temporal features from the noisy inertial sensor data. Second, while inter-subject gait features may show great separability, the intra-subject gait difference before and after HVLP may be significantly more subtle. Third, the variance in the collected data could also be reflecting the noise in neuromuscular control due to the different times of the day, environments, energy levels, or even moods of the patient. In other words, one could naturally (voluntarily or otherwise) change certain gait parameters instead of responding to HVLP. Fourth, new quantitative metrics must be established to assess certain gait characteristics that were assessed by visual observation previously.

To address these challenges and to explore the feasibility of extracting and leveraging advanced BSN-enabled gait features for enhanced separability in NPH diagnosis, a pilot study was performed on six suspected NPH patients with BSN data collection added to the gait assessment protocols before and after HVLP. To capture intra-personal NPH gait symptoms, methods for personalized signal processing – looking for changes in an individual's gait pre- to post-HVLP rather than extracting absolute measures – are designed. Nonlinear analysis techniques are used for characterizing gait instability – a gait deterioration character of NPH noted in the literature. Then gait features were extracted from inertial BSNs and compared before and after HVLP in order to evaluate the gait improvement and to identify gait features providing separability for NPH diagnosis.

The rest of this paper is organized as follows. Section 2 reviews the medical background and prevailing technology, states the motivation for this study, and identifies gait features for NPH diagnosis. Section 3 details the methodology for extracting such gait features using inertial BSNs. Section 4 presents the results of the pilot study on six suspected NPH patients using the methodology mentioned above. Section 5 directs the future plan for continuing this study, and Section 6 presents the conclusions of the study.

2. BACKGROUND

In order for an objective tool for aiding NPH diagnosis to be developed, the medical background of this condition must be understood. In this section, the medical aspects of NPH and its current clinical diagnosis procedure will be introduced. The state of the art technology for enabling high precision gait analysis will also be introduced.

2.1 Medical Research Review

2.1.1 Pathology

NPH is a neurological condition that takes one of two forms: secondary or idiopathic. Secondary NPH is the consequence of a preceding neurological trigger, such as meningitis, encephalitis, traumatic brain injury, brain hemorrhage, or any other process that may entail brain inflammation [11][12]. The diagnosis of secondary NPH can be done by noticing these precursors. On the other hand, Idiopathic NPH (INPH) has no identifiable antecedent. INPH is an adult-onset syndrome that generally affects elderly individuals. To date, its prevalence and incidence have only been estimated, primarily due to the difficulty of diagnosis. In the following text, the diagnosis focuses on INPH, and NPH will be used interchangeably as INPH.

In general, NPH is a condition that involves a CSF accumulation in the skull. The buildup of CSF is caused by one of two occurrences: either a blockage of the outward flow of CSF or a disturbance of CSF absorption [12]. In either case, CSF accumulates in the ventricles and/or the subarachnoid space of the brain. The increase of CSF causes an associated rise in intracranial pressure (ICP). In order to accommodate the elevation of intracranial pressure, the ventricles enlarge. This swelling is the first step in a chain of events responsible for one of the central paradoxes presented by NPH – the normal ICP. As the ventricular volume increases, so too does the ventricular surface area. As ventricular surface area grows, the pressure of excess fluid against the surfaces of the brain drops. Although there remains a surplus of CSF (hydrocephalus), the intracranial pressure equalizes, returning to normal.

2.1.2 Symptoms

The resulting symptoms of NPH manifest themselves as a characteristic triad of problems: dementia, urinary incontinence and gait disturbance. That NPH causes a form of dementia that is reversible with successful treatment reveals its second paradoxical element. The type of dementia experienced by NPH patients is subcortical. The cognitive processes affected are the patients' psychomotor skills, information processing, attention, memory/recall, visuospatial perception and visuoconstructive skills [1][12][13]. The severity of dementia varies by patient as well as by the length of time the patient has had NPH, another feature of the condition contributing to the difficulty of its diagnosis.

Although the changes in gait experienced by patients with NPH are not immune to the variability presented by other symptoms, gait impairment is a critical feature of NPH, since it is typically an obvious symptom and often appears in the early stages of the condition. This symptom, therefore, can profoundly impact diagnosis of NPH. The classic gait disturbance is sometimes described as "magnetic". It consists of a shuffling movement wherein the patient takes a wide stance, has a short step length and shows a reduced step height as though there were magnets in both the patient's feet and the floor. Other indications of gait disturbance include decreased cadence, an outward rotation of the feet, difficulty turning, a forward leaning posture, increased trunk sway, hesitant initiation of walking, and subtle impairments of arm movement [11][12][13].

2.1.3 Common Diagnosis Procedures

In order to make a diagnosis, the patient's history, a physical, brain imaging, and neurocognitive test results are considered. Particular attention should be paid to aspects of each symptom uncharacteristic of NPH, as they could rule out its diagnosis altogether.

The first step in diagnosing this condition may be brain imaging, such as magnetic resonance imaging (MRI) and X-ray computed

tomography (CT), as is most commonly presented in the NPH literature. While imaging alone cannot diagnose NPH, ventricular enlargement is a requirement for diagnosis. In addition to imaging, it is crucial to consider the patient's presenting symptoms.

Without the sensitivity of a neurocognitive evaluation, mild cognitive symptoms experienced by some NPH patients can escape detection. Thus, neuropsychological assessment is critical. Additionally, neuropsychological assessment can help distinguish among dementias of various types, such as Alzheimer's, dementia with Lewy bodies, frontotemporal dementia, vascular dementia, Parkinson's and the subcortical dementia that presents in patients with NPH.

Often times, especially in an elderly population, urinary problems can be attributed to a vast number of other conditions and can therefore confound the diagnosis of NPH. Symptoms range from urinary frequency and urgency to absolute incontinence. For example, because gait is impaired, it can be difficult to get to the restroom in a timely manner. Moreover, urinary incontinence appears rather late in the progression of symptom expression [11]. To avoid misdiagnosis, it is important to identify whether urinary dysfunction is due to urologic disorders, recurrent urinary tract infections in women, prostate problems in men, bladder dystonia/dysautonomia, urethral stricture, diuretic use, detrusor instability or pelvic floor weakness [11][12][13].

2.1.4 HVLP Procedure

Although there are three commonly used physiologic methods to test for NPH, the clinic at the University of Virginia typically performs an HVLP procedure, also known as a spinal tap. Typically, somewhere between 30 and 50 mL of CSF is removed. The patient must lie flat for an hour following the procedure after which the second cognitive and functional assessment is given. If the patient shows improvement, there is a chance that the patient will respond well to treatment. The benefits of this procedure include its ability to be completed on an outpatient basis, its current recommendation as one of the most accurate methods for diagnosis and its strong positive predictive value [12][13].

2.1.5 Current Clinical Evaluation Limitations

Prevailing clinical practice for evaluating ambulation function is still based on subjective clinical observation. More objective assessments usually adopt a stopwatch-timed 10 meter walk with a step count. The setup is easy to deploy in clinics and provides gait features such as gait speed and average step length and time. [5] and [14] have reported the increase of gait speed and stride length post-HVLP for patients ultimately diagnosed with NPH. However, this method has limitations. Due to the nonlinear nature of neuromuscular control in human beings, environmental noise could be introduced to the system as fluctuations in gait speed, stride length and stride time. In other words, gait kinematics could vary for adjusting to different environments, energy levels or even emotions.

These limitations are revealed in the pilot study described in detail in Section 4. Figures 1, 2, and 3 show the gait speed, average step length, and average stride time, respectively, of six patients (four of whom were later determined to have NPH) pre- and post-HVLP based on the timed 10 meter walk. These figures reveal that gait speed and step length do not always increase and stride time does not always decrease post-HVLP, indicating that these parameters do not provide good separability for gait-based NPH diagnosis.

This finding motivates the exploration of extracting other gait features for separating the NPH patients from the non-NPH patients, including features that cannot be extracted from visual observation alone.
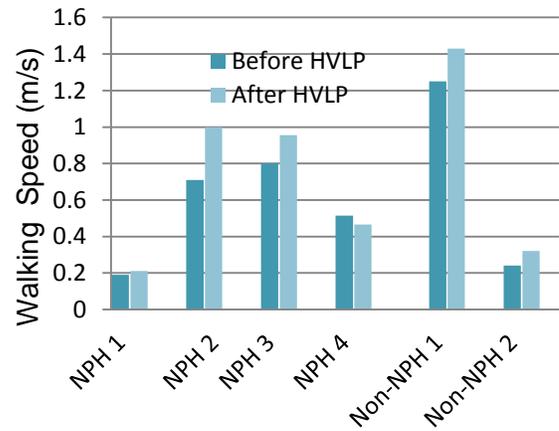

Figure 1. Gait speed change of suspected NPH patients pre- to post-HVLP does not provide NPH separability.
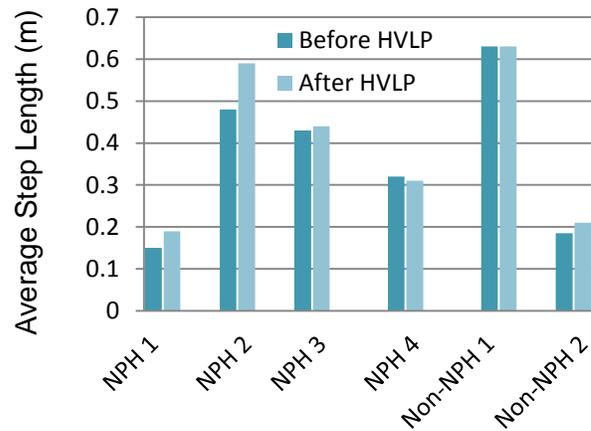

Figure 2. Average step length change of suspected NPH patients pre- to post-HVLP does not provide NPH separability.
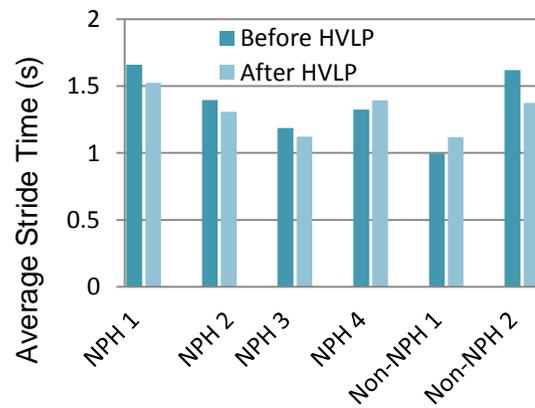

Figure 3. Average stride time change of suspected NPH patients pre- to post-HVLP does not provide NPH separability.

2.2 State of Art Technology Review

Higher precision gait analysis is available with optical motion capture systems such as Vicon®, which provide 3D position tracking. With a dedicated laboratory setup and biomechanical expert operation, the system provides accurate and precise spatial and temporal gait information such as joint angles, moment, power, and stride time. However, setting up such a gait lab in clinics can be expensive, and it is impractical for use on HVLP patients, who are impaired and fatigued and have already undergone significantly invasive procedures throughout the day.

More recently, inertial BSNs have been developed for non-invasive, accurate, wearable motion capture and gait analysis [7]. Research attempts using inertial BSNs for gait analysis have shown success in tracking gait parameters such as stride time variability and joint angle in long-term monitoring. Their capability of high precision motion capture and analysis make inertial BSNs an attractive option for pre- and post-HVLP gait assessment.

In this project, the TEMPO 3 inertial BSN research platform was employed [15]. TEMPO provides six degrees-of-freedom sensing from an arbitrary number of wristwatch-sized nodes distributed at strategic locations on the body. Sensors are sampled at 120Hz with up to 12-bit resolution. Data can be processed on-node with the MSP430F1611 mixed signal processor and then either transmitted wirelessly via Bluetooth® to a body-worn aggregator or stored locally in an on-node flash memory. While the wireless transmission capability enables in-clinic evaluation pre- and post-HVLP, emerging energy management schemes could enable gait monitoring over 24+ hours, providing outpatient in-home gait monitoring for follow-up evaluation. This future work will be detailed in Section 5.
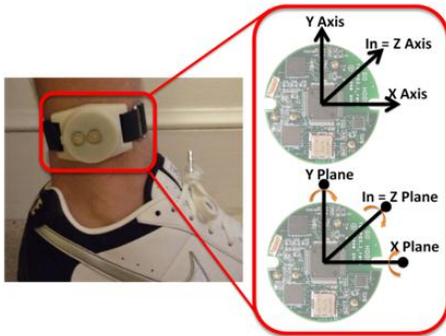

Figure 4. TEMPO inertial BSN platform, providing six degrees-of-freedom sensing in the form factor of a wristwatch.

3. METHODOLOGY

With this medical background and emergence of inertial BSNs for gait analysis, this section explores the extraction of features indicative of reversible gait abnormalities in NPH gait for diagnosis with inertial BSN data. Two types of features are explored – temporal and nonlinear.

3.1 Temporal Gait Features

Temporal information is commonly extracted from inertial BSNs. Compared to traditional gait analysis by observation, inertial BSNs can achieve high precision temporal information with its high sampling rate. More specifically, given accurately identified gait events as shown in Figure 5, inertial BSNs can provide highly accurate temporal information with sampling rates higher than

100Hz. In this section, the extraction of two temporal gait features (standard deviation of stride time and double stance time) will be described.
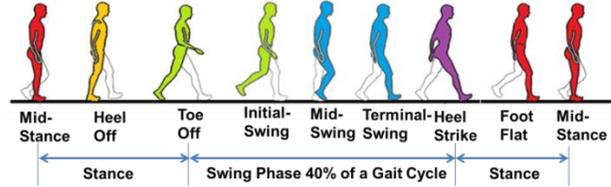

Figure 5. Human Gait Phases [6] adapted from [16]. Note: this figure does not represent the actual percentages of a gait cycle spent in each phase.

3.1.1 Stride Time Standard Deviation

Stride time variability is sometimes associated with gait stability [18]. Although average stride time can be obtained with a stopwatch and step counting, as described in Section 2.1.5, it does not provide information about cycle-to-cycle stride time. Greater accuracy, precision, and runtime of stride time assessment may be obtained by segmenting gait cycles. In this study, a peak detection algorithm is used to find the highest peak in the z-plane (sagittal) gyroscope signal (maximum shank angular velocity shown in Figure 6), which identifies the mid-swing event. To suppress the ripples in the gyroscope signal, a zero-phase, 3rd order, Butterworth low-pass filter with an empirically determined cutoff frequency of 3Hz is used, preventing the peak detection algorithm from selecting the random peaks due to ripples. After the gait cycles are extracted, the standard deviation of stride time is computed based upon the stride data obtained.
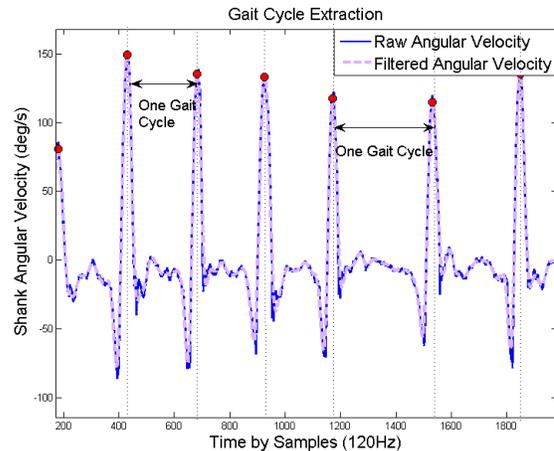

Figure 6. Gait cycle extraction from shank angular velocity.

3.1.2 Double Stance Time

[14] has reported significantly reduced average double support time in the NPH group after shunt surgery. Double stance time is the duration both feet are in contact with the ground. It can be counted as time from the heel-strike instance of one shank to the toe-off instance of the other shank. To find the toe-off event, the gyroscope signal is smoothed with a 3Hz low-pass filter. The toe-off instance is detected by finding the local minimum in a gait cycle using a peak detection algorithm (shown in Figure 7). Since some patients do not have distinct heel-strike peaks, the heel-strike is identified in the shank acceleration signal using a peak detection algorithm. The acceleration in the y-axis is low-passed filtered at

18Hz to remove some of the local maximum points due to noise. The heel-strike events are also plotted in Figure 7.
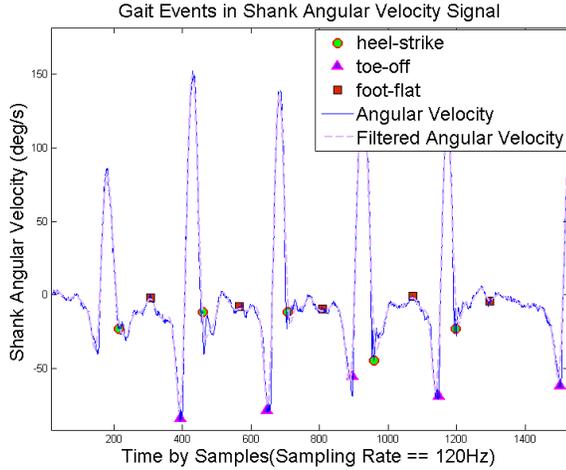

Figure 7. Gait events in shank angular velocity.

3.2 Nonlinear Gait Features

It is reported in [14] that the gait apraxia in NPH gait usually includes "poor balance, off balance, unsteady, wobbly, staggering, difficulty on stairs and curbs" with frequent falls. Since all these observations point to the instability of gait, we suspect that reversible abnormalities of NPH gait can be characterized by a measure of gait stability – an important feature for assessing walking balance and resulting fall risks [19][20].

To assess the stability of a dynamical system, nonlinear analysis tools have been adopted in biomechanics, such as the Poincaré return map [21] and Floquet number [20]. However, it is argued in [19] that due to the variance that exists in human motion, orbital stability assessment based on the assumption that human motion is strictly periodic is not a good measure. Instead, for pseudo-periodic systems as human movement, local stability can be used to describe how the dynamic system responds to "very small perturbations continuously in real time" [19]. Lyapunov exponent (LyE) is such a parameter to quantify the local stability.

3.2.1 Lyapunov Exponent

LyE is a parameter that characterizes gait stability with divergence of time series trajectories on the reconstructed phase portrait [19]. Higher positive LyE indicates lower gait stability. [22] has demonstrated that inertial sensors are valid for such analysis by finding a high correlation (0.98) between inertial sensors and optical motion capture systems on the largest LyE. [23], [24] and [22] concluded that the inferior body segment is more sensitive to a small perturbation than the superior segment, and they found a larger change in the LyE of shank angular velocity than the thigh angular velocity. Therefore, for this study, inertial BSN nodes were placed on the shank of the suspected NPH patients for expectation of higher separability in gait stability assessment than the thigh placement. To eliminate the temporal variations in the signal, the shank angle of one gait cycle is normalized temporally with a period of 120 samples.

To compute LyE for given time series data, the first two steps consist of finding the embedding dimension and time delay lag for phase space reconstruction. To find the embedding dimension of the time series, a False Nearest Neighbor (FNN) algorithm [25] is applied. With this algorithm, the time series of the shank's angular

position is identified to have an embedding dimension of 2. The time delay is determined by using average mutual information, and a time delay of 10 samples is used for computing LyE in this study.

After the phase space is reconstructed, LyE can be computed using either the W-algorithm [26] or the R-algorithm [25]. In gait analysis, the R-algorithm is more commonly used due to claimed accuracy on short-term data. However, [23] has argued that the W-algorithm is more appropriate for assessing local dynamic stability because of its sensitivity in estimating LyE. Since the purpose of this paper is separating the before and after HVLP gait parameters, higher sensitivity means better separability, thus the W-algorithm will be used. The equation for computing the largest LyE using the W-algorithm is shown in Equation (1) wherein λ_1 is the largest LyE in bits/seconds. Δt is the sampling period, in our case, 1/120 second. N is the total number of steps on the fiduciary trajectory. M is total number of replacement steps. $L'(i)$ and $L(i)$ are the distances between the vectors at the beginning and end of a replacement step, respectively.

$$\lambda_1 = \frac{1}{N \times \Delta t} \times \sum_{i=1}^{M} log_2 \frac{L'(i)}{L(i)} \tag{1}$$

In general, the W-algorithm tracks and quantifies the divergence of the nearest neighbors in the trajectories in the reconstructed phase space. First, it selects a fiduciary trajectory with a single nearest neighbor being followed and replaced when its separation $L'(i)$ from the fiduciary trajectory becomes large [23]. A new neighbor on the fiduciary trajectory is then selected to minimize the length $L(i)$ and the angular separation estimated by directional cosine value. This procedure is repeated until the fiduciary trajectory has gone over the entire data set. Then the largest LyE is estimated as in Equation (1).

4. EVALUATION

The above-mentioned methods were evaluated in a human subject pilot study with a focus on identifying the gait features that maximize separability for NPH diagnosis.

4.1 Experimental Setup

Data was collected on six suspected NPH patients pre- and post-HVLP. Subject consent and assent was approved by the University of Virginia's IRB and obtained for all patients. Existing methods for cognitive and functional assessment were used, but TEMPO data collection was added to the 10 meter walk. TEMPO nodes were placed on both wrists, both shanks and the waist, as shown in Figure 8. The inertial sensor data was streamed via Bluetooth® to a portable laptop carried by a technician following the patients. All data collected was post-processed and analyzed in Matlab®.

A neurosurgeon inspected the suspected patients after their cognitive and functional assessments were completed pre- and post-HVLP, and decisions were made about prescribing the VP shunt or ruling out NPH. Due to the risk of missing possible NPH patients whose quality of life could be dramatically improved through a VP shunt, neurosurgeons tend to err on the side of shunting boarderline cases, which presumably results in a low number of false negative diagnoses. (Note: the number of false negatives cannot be determined.) However, patient follow-up is necessary to identify any false positive diagnoses, which would be apparent from lack of a positive response to the VP shunt placement.

According to the follow-up information for this study, the four patients diagnosed as NPH have regained non-negligible cognitive

and functional ability after the shunt surgery, confirming the correctness of the diagnosis (i.e., true positives). Given that the gait data available to the neurosurgeons (gait speed, average stride time, and average stride length) would not have resulted in these accurate diagnoses (see Figures 1-3), the cognitive assessments, which were not considered in this study, must have provided the necessary separability. The objective of this study was to identify the BSN-enabled gait features that *would have* provided that separability, too. Note: this is clearly a small, underpowered pilot study, and the results must be considered accordingly. However, the following analysis is suggestive of the potential of using BSNs for NPH diagnosis.


Figure 8. Suspected NPH patient walking in the clinic hallway. Inertial BSN nodes are placed on the wrists, lower shanks and back of waist.

4.2 Results

Using the methods described in Section 3, stride time standard deviation, average double stance time, and stability (via LyE) were extracted from the TEMPO data collected during the 10 meter walk.
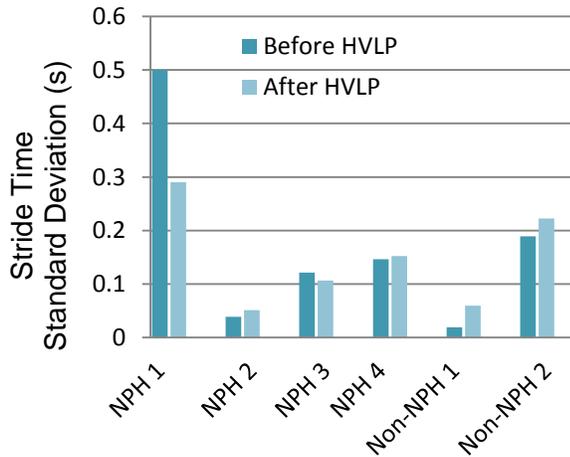
Figure 9. Stride time standard deviation change of suspected NPH patients pre- to post-HVLP does not provide NPH separability.
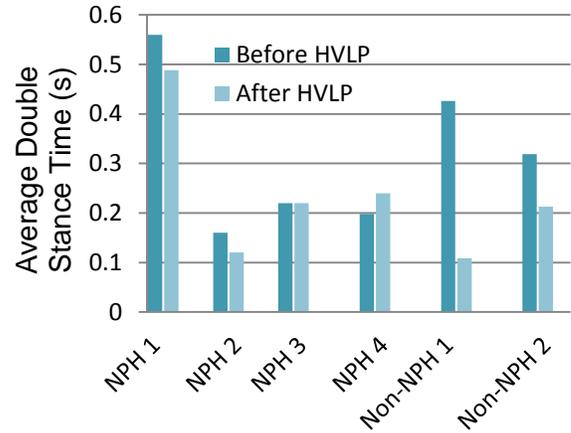
Figure 10. Average double stance time change of suspected NPH patients pre- to post-HVLP does not provide NPH separability.
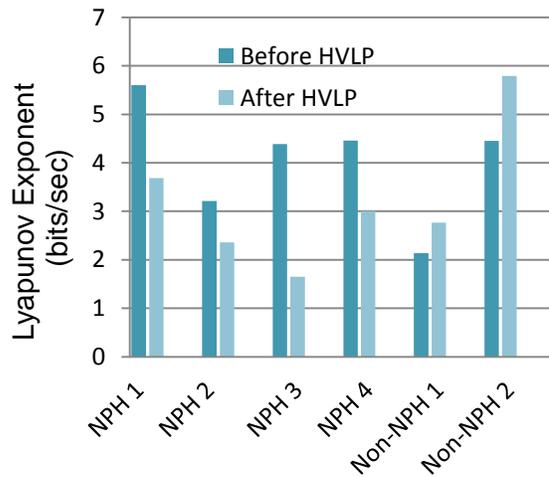
Figure 11. LyE change of suspected NPH patients pre- to post-HVLP *does* provide NPH separability (NPH patients improved post-HVLP (i.e., lower LyE), while non-NPH patients deteriorated), indicating its potential to aid in NPH diagnosis.

Higher stride time standard deviation indicates a higher temporal variability between strides, as suggested in [18]. However, the results shown in Figure 9 reveal that stride time standard deviation does not provide separability between the NPH and non-NPH patients (comparing intra-subject pre- to post-HVLP improvements).

Higher average double stance time typically indicates issues with stability and balance, but the results in Figure 10 show that this feature does not always decrease after HVLP for the NPH patients and thus does not provide the desired separability for NPH diagnosis.

However, Figure 11 reveals that all diagnosed NPH patients see a significant post-HVLP improvement in stability (i.e., a decrease of LyE), and the non-NPH patients see no such improvement and even degradation (attributed clinically to fatigue). LyE therefore provides the desired NPH separability. To find statistical meaning in this preliminary finding, a two way ANOVA analysis was done

on each gait feature extracted from above, and LyE was the only parameter that found before and after difference in the shunted group (p<0.025). This pilot data had an effect size greater than 1, suggesting that a meaningful conclusion can be obtained with about 10 subjects in each group in future studies.

4.3 Discussion

The results in Figures 9-11 suggest that stability quantified by LyE is a good gait parameter for evaluating the HVLP response. Of all the parameters extracted, LyE provides the best separability for classifying those who are highly likely to have NPH and those who are not. It is again worth noting that this research merely provides promising pilot results. Ultimately, a large-scale study is needed to further evaluate these and other BSN-enabled gait features for NPH diagnosis and other neuropsychological diseases.

As noted in Section 2.1.5, conventional observation-based gait parameters did not provide such separability. Though many researchers have found that gait speed and stride length are important parameters for diagnosis of NPH, the change in gait speed did not correlate well with the neurosurgeon's diagnoses. This could be due to two reasons. First, the 10 meter stopwatch method for assessing gait speed is not entirely accurate because of the reasons introduced in Section 2. Second, the patients may need to adjust gait speed to increase stability, and usually this adjustment is achieved by slowing down in the elderly, as argued in [27] and [28]. Variability assessment of stride time and stride length also do not correlate with diagnosis, as is corroborated in [27] and [28].

5. FUTURE WORK

To further validate the results found this paper, a greater number of subjects are needed, and additional patient monitoring is desirable. Since traditional neurocognitive and gait assessments are performed by professionals, inpatient monitoring or multiple outpatient visits are required for any extended post-HVLP evaluation. TEMPO and other inertial BSNs provide the potential for continuous, longitudinal gait assessments, and subsequent studies will therefore include protocols for both in-clinic and out-of-clinic data collections using TEMPO. TEMPO's ability to interchange the Bluetooth® transmission module with a flash memory will be leveraged for this purpose. The in-clinic data collections will use Bluetooth®, which enables the nurses or physicians conducting the data collection to annotate the streaming data to provide extra information for later analysis, and the out-of-clinic collections will use the flash memory, which provides higher reliability and longer battery life and will save data for later download and analysis. This longer, out-of-clinic monitoring may provide more natural and representative data, and gait features that assess average gait performance, such as gait speed, may be more meaningful to evaluate gait performance. [6] and [8] have shown the possibility of extracting gait speed accurately with a resolution of 0.09m/s with inertial BSNs. However, technical challenges that must be overcome for this future study include controlling for the numerous variables that are injected into unstructured, out-of-clinic BSN data collections, such as walking surface, foot apparel, walking purpose, etc.

The methodology should also be evaluated in terms of the clinical practice. Although the wireless sensor solution ensures the ease of the deployment in a clinical setting, currently, the medical research staff is instructed follow a protocol to set up the experiment, including correctly mounting the sensor in order for it to be aligned with the sagittal plane. In the future, to better provide accuracy with less strict placement procedures, simple mounting calibration procedures can be adopted. In addition, to fully realize the utility of this method, clinical interfaces should be developed to provide automated visualization and interpretation of the data. With results validated in larger group studies, gait stability and other gait features extracted from inertial sensor data can be included as critical parameters for aiding clinical decision.

6. CONCLUSIONS

In this paper, a pilot study was conducted to explore the use of BSN-enabled gait features to aid the diagnosis of NPH. With inertial BSN measurement, more objective, quantitative and precise gait features can be extracted, including stride time standard deviation, average double stance time and local dynamic stability (assessed by LyE). Results from this small study suggest that LyE provides better separability than currently used gait features for NPH diagnosis when comparing gait performance pre-to post-HVLP. In addition, the results raise the potential for the use of inertial BSNs for out-of-clinic gait analysis to further improve NPH diagnosis and to enable other medical applications that would benefit from longer term outpatient monitoring of gait performance.

7. ACKNOWLEDGMENTS

8. REFERENCES

[1] G. D. Rigamonti and M. A. Williams. The diagnosis and treatment of idiopathic normal pressure hydrocephalus. *Nature Clinical Practice Neurology*, 2(7):375-381, 2006.

[2] A. Brean and P. K. Eide. Prevalence of probable idiopathic normal pressure hydrocephalus in a Norwegian population. *Acta Neurologica Scandinavica,* 118(1):48-53, 2008.

[3] N. Tanaka, S. Yamaguchi, H. Ishikawa, H. Ishii and K. Meguro. Prevalence of possible idiopathic normal-pressure hydrocephalus in Japan: the Osaki-Tajiri project. *Neuroepidemiology*, 32(3):171-5,2009.

[4] A. Shrinivasan, M. Brandt-Pearce A. T. Barth, and J. Lach. Analysis of gait in patients with normal pressure hydrocephalus. *International Workshop for Mobile Systems, Applications, and Services for Healthcare*, pages 3:1-6, 2011.

[5] P. Bugalho and J. Guimares. Gait disturbance in normal pressure hydrocephalus: A clinical study. *Parkinsonism and Related Disorders*, pages 13:434–437, 2007.

[6] S. Chen, C. Cunningham, B. C. Bennett, and J. Lach. Extracting spatio-temporal information from inertial body sensor networks for gait speed estimation. *International Conference on Body Sensor Networks,* pages 71–76, 2011.

[7] S. Chen, C. L. Cunningham, B. C. Bennett, and J. Lach. Enabling longitudinal assessment of ankle-foot orthosis efficacy for children with cerebral palsy. *Wireless Health*, pages 4:1-10, 2011.

[8] X. Xu, M. A. Batalin, W. J. Kaiser and B. Dobkin. Robust hierarchical system for classification of complex human mobility characteristics in the presence of neurological disorders. *International Conference on Body Sensor Networks*, pages 65-70, 2011.

[9] L. Atallah, G. J. Jones, R. Ali, J. Leong, B. Lo and G-Z. Yang. Observing recovery from knee-replacement surgery by using wearable sensors. *International Conference on Body Sensor Networks*, pages 29-34, 2011.

[10] I. Tien, S. D. Glaser, R. Bajcsy, D. S. Goodin and M. J. Aminoff. Results of using a wireless inertial measuring system to quantify gait motions in control subjects. *IEEE Transactions on Information Technology in Biomedicine*, 14(4):904-915, 2010.

[11] D. Tsakanikas and N. Relkin. Normal pressure hydrocephalus. *Seminars in Neurology*, 27(1):58-65, 2007.

[12] R. K.Wilson and M. A. Williams. Normal pressure hydrocephalus. *Clinics in Geriatric Medicine*, 22:935-951, 2006.

[13] N. R. Graff-Radford. Normal pressure hydrocephalus. *Neurologic Clinics*, 25:809-832, 2007.

[14] M. A. Williams, G. Thomas, B. de Lateur, H. Imteyaz, J. G. Rose, W. S. Shore, S. Kharkar, and D. Rigamonti. Objective assessment of gait in normal-pressure hydrocephalus. *American Journal of Physical Medicine and Rehabilitation*, pages 2–3, 2007.

[15] A. T. Barth, M. A. Hanson, H. C. Powell Jr., and J. Lach. TEMPO 3.1: A body area sensor network platform for continuous movement assessment. *International Workshop on Wearable and Implantable Body Sensor Networks*, pages 71-76, 2009.

[16] Q. Li, M. Young, V. Naing, and J. M. Donelan. Walking speed and slope estimation using shank mounted inertial measurement units. *Journal of Biomechanics*, 43(8):1640-1643, 2010.

[17] K. L. Warnecke. Analysis of gait before and after cerebrospinal fluid lumbar tap test in idiopathic normal pressure hydrocephalus: a literature review and case report. *Topics in Geriatric Rehabilitation,* 25(3):203-210, 2009.

[18] L. D. Ravdin, H. L. Katzen, A. E. Jackson, D. Tsakanikas, S. Assuras, and N. R. Relkin. Features of gait most responsive to tap test in normal pressure hydrocephalus. *Clinical Neurology and Neurosurgery*, 110(5):455-461, 2008.

[19] J. B. Dingwell and J. P. Cusumano. Nonlinear time series analysis of normal and pathological human walking. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 10(4):848-886, 2000.

[20] K. P. Granata, T. E. Lockhart. Dynamic stability differences in fall-prone and healthy adults. *Journal of Electromyography and Kinesiology*, 18(2):172-178, 2008.

[21] Y. Hurmuzlu, C. Basdogan, and J. J. Carollo. Presenting joint kinematics of human locomotion using phase plane portraits and Poincaré maps. *Journal of Biomechanics*, 27(12):1495-1499, 1994.

[22] S. M. Bruijn, D. J. J. Bregman, O. G. Meijer, P. J. Beek, and J. H. van Dieën. Estimating dynamic gait stability using data from non-aligned inertial sensors. *Annals of Biomedical Engineering*, 38(8):2588-2593, 2010.

[23] F. Cignetti, L. M. Decker, and N. Stergiou. Sensitivity of the Wolf's and Rosenstein's algorithms to evaluate local dynamic stability from small gait data sets. *Annals of Biomedical Engineering*, 40(5):1122-1130, 2011.

[24] H.G. Kang and J. B. Dingwell. Dynamic stability of superior vs. inferior segments during walking in young and older adults. *Gait and Posture*, 30(2):260-263, August 2009.

[25] M. T. Rosenstein, J. J. Collins, and C. J. De Luca. A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D* 65:117–134, 1993.

[26] A. Wolf, J. B. Swift, H. L. Swinney, and J. A. Vastano. Determining Lyapunov exponents from a time series. *Physica D*, 16:285-317, 1985.

[27] S. A. England and K. P. Granata. The influence of gait speed on local dynamic stability of walking. *Gait and Posture*, 25(2):172-178, 2007.

[28] J. B. Dingwell and H. G. Kang. Differences between local and orbital dynamic stability during human walking. *Journal of Biomechanical Engineering*, 129(4):586-593, 2007.