Automated Health Alerts from Kinect-based In-Home Gait Measurements

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***Abstract*—A method for automatically generating alerts to clinicians in response to changes in in-home gait parameters is investigated. Kinect-based gait measurement systems were installed in apartments in a senior living facility. The systems continuously monitored the walking speed, stride time, and stride length of apartment residents. A framework for modeling uncertainty in the residents' gait parameter estimates, which is critical for robust change detection, is developed; along with an algorithm for detecting changes that may be clinically relevant. Three retrospective case studies, of individuals who had their gait monitored for periods ranging from 12 to 29 months, are presented to illustrate use of the alert method. Evidence suggests that clinicians could be alerted to health changes at an early stage, while they are still small and interventions may be most successful. Additional potential uses are also discussed.**

I. Introduction

A growing amount of research has demonstrated the importance of measuring an individual's gait [1] and that the parameters which describe locomotion are indispensable in the diagnosis of frailty and fall risk [2]. Studies have found that certain gait parameters may be predictive of future falls and adverse events in older adults [3, 4], and that gait parameters may change prior to cognitive impairment [5, 6].

Although research suggests assessment of gait is valuable for a variety of purposes, it is generally assessed infrequently, if at all, in a clinician's office or performance lab, and only a small number of walks are typically observed. This infrequent assessment with a small number of observations, in combination with high levels of intra-individual test-retest variability, leads to large minimum detectable change (MDC) values being reported for detecting changes in individuals, especially frail older adults [7]. Thus, despite studies indicating gait parameters are good population level indicators, they have shown less promise for detecting small changes in an individual.

Every day, continuous measurement based on five to ten, or more, walks per day could allow detection of more subtle change in an individual's gait that may be an early indicator of significant changes (such as mild cognitive impairment) in health status. Detecting health changes early would allow for timely use of interventions when they may be most successful. Ideally, environmentally mounted sensors that do not require active participation of the individual, and do not require any devices to be worn, would be used given the preferences of older adults [8].

In [9], the authors developed a method for measuring walking speed continuously in home environments using an array of passive infrared sensors. In subsequent studies [6, 10], the authors found statistically significant associations between in-home walking speed and conventional measures of walking speed and gait-related motor function. They also showed that walking speed may be an early marker of the development of mild cognitive impairment. More recently, in [11], a method for measuring walking speed, stride time, and stride length continuously in home environments using the Microsoft Kinect [13] was developed.

This paper details initial investigation of a method for automatically generating alerts to clinicians in response to changes in in-home gait parameters measured using the method in [11]. Automatically identifying and alerting clinicians to potentially relevant changes in gait removes the need for them to continuously scrutinize the data. After receiving an alert, clinicians could analyze the data to determine if an intervention is warranted.

Section II of this paper gives a brief overview of the Kinect-based in-home gait measurement system, followed by a description of both the framework used to model uncertainty in the in-home gait parameter estimates and the automated health alert algorithm. Section III presents three retrospective case studies illustrating use of the health alert algorithm. Finally, Section IV contains a brief discussion of the results, along with avenues for future investigation.

II. Methodology

A. Brief System Overview

Fig. 1 shows the Kinect-based gait measurement system installed in one apartment included in the study. A Kinect is placed on a small shelf below the ceiling (height 2.75 meters), and a computer is placed in a cabinet above the refrigerator. Walking segments occurring in view of the systems are automatically identified, segmented, and analyzed, and a probabilistic model representing each resident's in-home gait is created and updated over time. Readers are referred to [11] for a more detailed description.

B. Modeling Uncertainty in Gait Parameter Estimates

The method in [11] for estimating in-home gait parameters does not attempt to quantify uncertainty in the estimates. However, the level of uncertainty has significant

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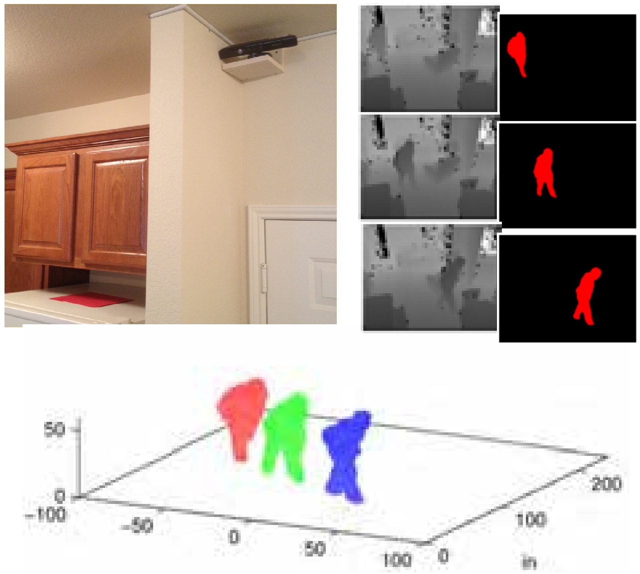

Fig. 1 **Top Left:** Kinect and computer (inside cabinet) as installed. **Top Right:** Depth images and extracted foreground from an apartment. **Bottom:** Three-dimensional object formed using extracted foreground (all dimensions in inches).

implications for implementing a robust automated health alert algorithm. Uncertainty is introduced in both steps of the estimation process: (1) modeling a resident's habitual gait, and (2) parameter estimate calculation. To quickly review, it is assumed that a resident will create a mode in the 4D data (height, stride time, stride length, walking speed) captured in their home. Step one fits a Gaussian distribution to the mode of each resident; typically using one to three months of data depending on how frequently walks from the resident are captured. Step two then computes parameter estimates for a resident over a desired time period, typically three days to two weeks, by selecting data points that are likely from the resident given their model, and then taking the mean of those selected points.

For this analysis, it will be assumed the underlying assumption that a resident's walk data follows a Gaussian distribution in the feature space is correct. Based on work using a set of hand labeled walk data [12], this assumption seems reasonable. Thus, the uncertainty in the estimation process is dependent on two factors, the number of walks captured from the resident, and the level of data corruption; where data corruption refers to overlap between the Gaussian distribution of a resident and that of other individuals. Although the presence and degree of data corruption could be significant in certain situations, it will be assumed for this analysis that no significant overlap exists. Again, based on [12], this assumption also seems reasonable for single resident homes, and multi-resident homes in which the residents differ considerably in height.

As a resident's walks are drawn from a Gaussian distribution, uncertainty in the mean can be quantified by the standard error of the sample mean (*SEM*):

$$SEM = \frac{\sigma}{\sqrt{N}} \tag{1}$$

where σ is the sample standard deviation, and N is the sample size. Given SEM, 95 percent confidence limits of parameter estimate μ can be computed as:

$$95\%\ limits = \mu \pm 1.96\, SEM \tag{2}$$

Uncertainty in the final parameter estimates depends on both the SEM for step two, SEM_p, and the SEM for step one, SEM_m. The impact of SEM_m depends on the threshold, T_s, used to select data. If all data points with a Mahalanobis distance of 4 or less to a resident's distribution were selected for inclusion in step two, less than 1 percent of the walks from the resident should be excluded, and the impact of SEM_m should be negligible. However, if only data points with a Mahalanobis distance of 1 or less to a resident's model were selected, roughly one third of the walks from the resident should be excluded. As a result, selection bias resulting from error in step one could have a significant impact on the final parameter estimates. Consequently, uncertainty in the final estimates, SEM_f, may be modeled as:

$$SEM_f = SEM_p + f(T_s)SEM_m \tag{3}$$

where T_s is the threshold in Mahalanobis distance used to select walks for inclusion in step two.

Monte Carlo simulation was used to approximate $f(T_s)$. The simulation process consisted of:

1) randomly generate a Gaussian distribution modeling a resident, $\theta_r = g_r(x|\mu_r,\Sigma_r)$
2) draw a random number of data points from θ_r, denote this set of points as χ
3) fit a model, ϕ, to χ as described in [11]
4) pick a random sub-sample, Υ, of χ
5) select a subset, β, of Υ based on ϕ and $T_s = t$
6) compute parameter estimates, μ_e, as the mean of β

Following completion of these steps, μ_e and μ_r were stored, along with SEM_p and SEM_m.

Using the results of 20,000 simulations, the value of $f(t)$ was computed as that needed to make the distribution of s_i:

$$s_i = \frac{\mu_e - \mu_r}{SEM_f} = \frac{\mu_e - \mu_r}{SEM_p + f(t)SEM_m} \tag{4}$$

have a standard deviation of 1. Results for varying values of T_s are shown in Fig. 2. On the interval [1,4], $f(T_s)$ can be closely approximated as a best fit line:

$$f(T_s) = -0.153T_s + 0.641 \tag{5}$$

Thus, 95 percent confidence limits for in-home gait parameter estimate μ may be approximated as:

$$95\%\ limits = \mu \pm 1.96\, SEM_f \tag{6}$$

$$= \mu \pm 1.96\left[\frac{\sigma_p}{\sqrt{N_p}} + \frac{\sigma_m(0.641 - 0.153T_s)}{\sqrt{N_m}}\right]$$

where σ_x and N_x are the sample standard deviation and sample size for each step in the estimation process, and T_s is in the range [1,4].

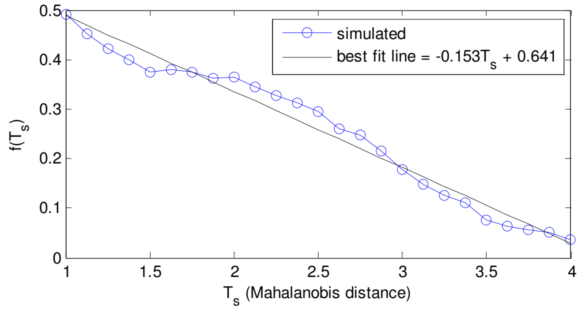

Fig. 2. Monte Carlo simulation results for approximating $f(T_s)$. Each point was computed using the results of 20,000 simulations.

C. Health Alert Algorithm

The goal of the alert algorithm is to detect changes in a resident's gait which may be indicative of changes in health status. The health alert algorithm effectively serves as a summarization mechanism; alerting clinicians to what may be significant data points while removing the need for the clinicians themselves to continuously scrutinize the data.

First, a baseline, in the form of a range, B, is computed for each parameter as:

$$B = [\hat{\mu}_B(1-\Delta_l) - \sigma_B, \hat{\mu}_B(1+\Delta_u) + \sigma_B] \tag{7}$$

where Δ_l and Δ_u determine the percentage change required to trigger an alert, $\hat{\mu}_B$ is the average value of the parameter estimate over the most recent four weeks, and σ_B is the average value of $1.96SEM_F$ for the parameter over the most recent four weeks. After computation, the baseline stays fixed until an alert is generated.

The parameters Δ_l and Δ_u may be tuned by clinicians based on the level of change they deem significant. Ultimately, smaller values will lead to more alerts, while larger values will lead to fewer. For the case studies in Section III, values of 0.015 and 0.035 were selected for Δ_l and Δ_u, respectively, to achieve a suitable number of alerts.

A current range, C, is computed every night as:

$$C = [\hat{\mu}_c - \sigma_c, \hat{\mu}_c + \sigma_c] \tag{8}$$

where $\hat{\mu}_C$ is the average value of the parameter estimate over the most recent week, and σ_C is the average value of $1.96SEM_F$ for the parameter over the most recent week. If C does not overlap B, an alert is generated.

Following an alert, the baseline is recomputed using the most recent four weeks of data prior to the day of the alert. New alerts are then suppressed for one week, limiting alert frequency to a maximum of one per week.

III. Results

Three retrospective case studies are included to illustrate the alert algorithm. The three individuals were monitored as part of an IRB approved study and informed consent was obtained from all. Each had a Kinect-based gait measurement system [11] installed in their home. Gait parameter estimates are shown for each individual in Fig. 3, and alerts that would have been generated are overlaid.

A. Case Study 1

This individual was monitored from October 3, 2011, until present, roughly 29 months. Over this period, 12 alerts would have been generated.

On July 7, 2012, this individual started medication for back and shoulder pain. He was out of his home for knee surgery from Oct. 12, 2012, until Oct. 29, 2012. After returning, he continued physical therapy until Nov. 21, 2012. On Dec. 17, 2012, he reported intense back spasms, and restarted physical therapy until Jan. 8, 2013.

Alerts 1 and 2, generated July 18, 2012, and Sep. 10, 2012, respectively, were due to decreased stride length. These alerts likely indicate declining physical function after he started pain medication July 7, 2012.

Alert 3, generated Nov. 21, 2013, was due to increased stride time, decreased stride length, and decreased gait speed following the individual's return after knee surgery. The lag between the time the alert was generated and the individual's return, 23 days, is a result of the Gaussian model needing to first adapt to the drastic change before a week's worth of data matching the model could be acquired to compute current range, C.

Alerts 4 through 8, generated over the time period Jan. 3, 2013 through Feb. 15, 2013, were all due to decreasing stride time and increasing gait speed. These alerts indicate a quick, continuing improvement in physical function during, and for the month following, additional physical therapy from Dec. 17, 2012, through Jan. 8, 2012. Although improvement slowed, alerts 9 and 10, generated May 10, 2013, and June 28, 2013, respectively, due to increasing gait speed, indicate continued improvement.

Alerts 11 and 12, generated Aug. 26, 2013, and Sep. 2, 2013, due to decreased gait speed, indicate a slight decline in physical function following this individual's return from a vacation. Extended periods of time spent sitting in cars and on planes can lead to muscle weakness, and there is often a period of adjustment when transitioning back into one's normal routine. This individual's gait speed appears to have continued to decrease slightly over the most recent 6 months; however, the change has not been sufficient to trigger another alert.

B. Case Study 2

This individual was monitored from October 8, 2011, through September 23, 2012, roughly 12 months. Over this period, 15 alerts would have been generated.

On May 17, 2012, this individual was admitted to the hospital for an inpatient psychiatric examination to evaluate his mental status and adjust medication. He returned home May 31, 2012, after his mental condition was stable. Mental health interventions included an added antidepressant for mood stabilization and sleep regulation in addition to regular outpatient visits with a Geriatric Psychiatrist.

Alerts 1 through 7, generated over the time period Dec. 20, 2011, through Mar. 8, 2012, all due to decreased gait speed, predate the inpatient evaluation by 2 to 5 months.

Alerts 8 through 15, generated over the time period Aug. 3, 2012, through Sep. 22, 2012, all due to decreased stride length and/or gait speed, correspond to progression of dementia, with the individual becoming increasingly agitated in the environment. This individual was discharged from the study when he moved to a facility specific to Alzheimer's.

C. Case Study 3

This individual, who was diagnosed with Parkinson's several years prior to enrollment in the study, was monitored from October 8, 2011, through September 23, 2012. Over this period, 8 alerts would have been generated.

This individual was a relatively frequent faller, suffering 8 recorded falls in the 18 months prior to the study. However, fall frequency increased near the end of March, 2012, as she suffered 15 recorded falls in the 6 months prior to being discharged from the study. She also had several medication adjustments during July, 2012, before a combination that worked well for her symptoms was found.

Alerts 1 and 2, generated Jan. 8, 2012, and April 23, 2012, respectively, due to decreased gait speed, correspond to continued progression of Parkinson's, with the first alert predating the increased fall frequency by 2 months.

Alerts 3 through 8, generated over the time period June 12, 2012, through Aug. 17, 2012, all due to either increased stride time, decreased stride length, and/or decreased gait speed, correspond to continued functional decline until successful medication adjustment likely resulted in a plateau during her final month in the study.

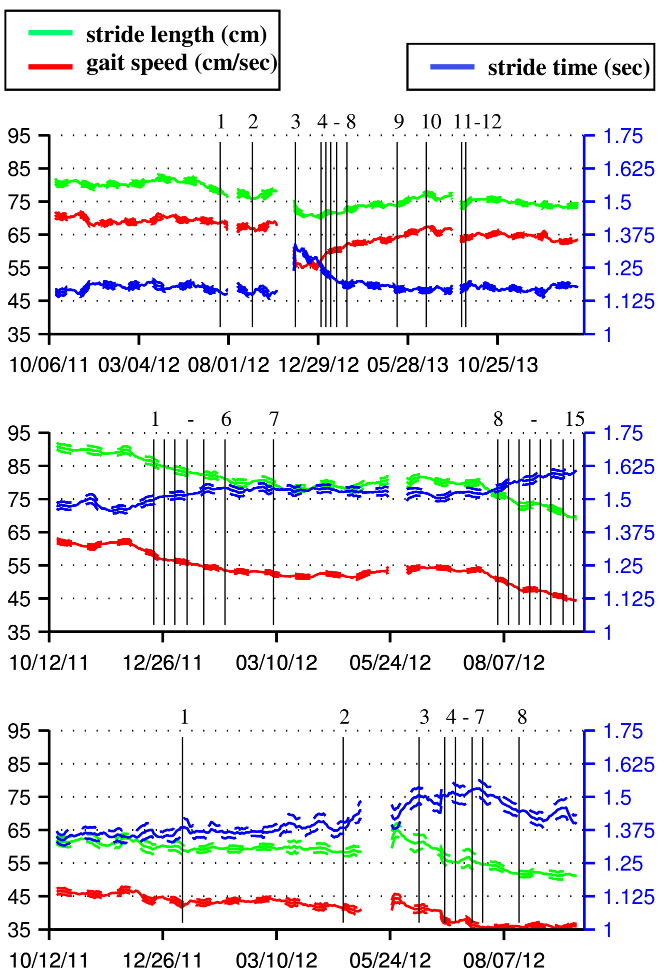

Fig.3. Graphs (with 95% intervals) of in-home gait parameters. Gaps indicate periods when individual was out of home, or did not walk frequently enough to be modeled. Vertical lines indicate alerts that would have been generated. Refer to Section III for specific discussion of the alerts. **Top:** Case study 1. **Middle:** Case study 2. **Bottom:** Case study 3.

IV. Discussion

An automated health alert algorithm was retrospectively applied to in-home gait data collected from three individuals. These case studies illustrate the potential of automated alerts based on in-home gait data for notifying caregivers of changes in an individual's gait that may be indicative of changes in health status. This includes the onset or further progression of mental health issues. Such alerts could also help caregivers track changes in an individual following surgery, medication adjustment, or other interventions. Finally, the ability to accurately compare an individual's gait before and after a major event, such as knee surgery, offers an improved method for evaluating the pace of recovery and final outcome.

Future work includes further investigation and refinement of the automated health alert algorithm, along with real-time use of the alerts in an upcoming study. This prospective study will investigate many issues not addressable with a retrospective analysis.

References

[1] D. Hodgins, "The Importance of Measuring Human Gait," Medical Device Technology, 19(5):42, 44-7, 2008.

[2] M. Runge and G. Hunter, "Determinants of musculoskeletal frailty and the risk of falls in old age," Journal of Musculoskeletal and Neuronal Interactions, 6:167–173, 2006.

[3] JM Hausdorff, DA Rios, and HK Edelberg, "Gait variability and fall risk in community-living older adults: a 1-year prospective study," Arch Phys Med Rehabilitation, 82:1050–6, 2001.

[4] M. Montero-Odasso et al., "Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older," J. of Gerontol. A Biol. Sci. Med. Sci., 60:1304–9, 2005.

[5] R. Camicioli, D. Howieson, B. Oken, G. Sexton and J. Kaye, "Motor slowing precedes cognitive impairment in the oldest old," Neurology 50:1496–1498, 1998.

[6] H.H. Dodge et al., "In-home walking speeds and variability trajectories associated with mild cognitive impairment," Neurology, 78(24):1946-52, 2012.

[7] K. Mangione et al., "Detectable changes in physical performance measures in elderly African Americans," Physical Therapy, 90(6):921-927, 2010.

[8] G. Demiris et al., "Older Adults' Attitudes Towards and Perceptions of 'Smarthome' Technologies: a Pilot Study," Medical Informatics and The Internet in Medicine, 29(2):87-94, 2004.

[9] S. Hagler, D. Austin, T. Hayes, J. Kaye, and M. Pavel, "Unobtrusive and Ubiquitous In-Home Monitoring: A Methodology for Continuous Assessment of Gait Velocity…," IEEE Trans. Biomed Eng., 2009.

[10] J. Kaye et al., "One walk a year to 1000 within a year: Continuous in-home unobtrusive gait assessment of older adults," Gait and Posture, 35(2), pp. 197-202, 2012.

[11] E. Stone and M. Skubic, "Unobtrusive, Continuous, In-Home Gait Measurement Using the Microsoft Kinect," IEEE Trans. on Biomed Eng., 60(10):2925-32, 2013.

[12] E. Stone and M. Skubic, "Passive, In-Home Gait Assessment Using an Inexpensive Depth Camera: Initial Results," ICST 6th Int. Conf. on Pervasive Computing Tech. for Healthcare, 2012.

[13] Z. Zhang, "Microsoft Kinect sensor and its effect," IEEE MultiMedia, 19(2):4-10, 2012.