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# Unobtrusive Monitoring of the Longitudinal Evolution of In-Home Gait Velocity Data with Applications to Elder Care

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## Abstract

Gait velocity has repeatedly been shown to be an important indicator and predictor of both cognitive and physical function, especially in elderly. However, clinical gait assessments are conducted infrequently and cannot distinguish between abrupt changes in function and changes that occur more slowly over time. Collecting gait measurements continuously in-home has recently been proposed and validated to overcome these clinical limitations. In this paper, we describe the longitudinal analysis of in-home gait velocity collected unobtrusively from passive infrared motion sensors. We first describe a model for the probability density function of the in-home gait velocities. We then describe estimation of the evolution of the density function over time and report empirically determined algorithm parameters that have performed well over a wide variety of different gait velocity data. Finally, we demonstrate how this approach allows detection of significant events (abrupt changes in function) and slower changes over time in gait velocity data collected from a sample of two elderly subjects in the Intelligent Systems for Assessing Aging Changes (ISAAC) study.

## I. Introduction

Gait velocity has been repeatedly shown to be an important predictor and indicator of both cognitive and physical function. Gait velocity has been successful at predicting dementia [1, 2], cognitive decline [3], future disability [4], and future risk of hospitalization [5],

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especially in aging populations. Other studies have demonstrated a link between gait velocity and both executive function [6, 7] and cognition [8, 9].

Despite the abundant evidence supporting gait velocity as an important measure of an individuals' well being and health status, in practice gait velocity is typically assessed infrequently – often a year or more passes between assessments - and only in a clinical setting. This clinical based gait assessment methodology suffers from several shortcomings including the inability to differentiate between abrupt changes in function and slower changes occurring over time. Additionally, several visits are generally required before variability (which may also be an important indicator of function) in gait velocity can be accurately assessed. One approach to overcome these limitations using passive infrared motion sensors to measure gait velocity unobtrusively in the home setting was recently proposed and validated [10].

This in-home monitoring technology was developed in the context of the Intelligent Systems for Assessing Aging Changes (ISAAC) study described in detail elsewhere [11]. Briefly, the ISAAC study seeks to use home-based unobtrusive sensor technology in wireless networks to monitor activity patterns such as gait velocity, general activity, and time-out-of-home to detect changes in cognitive, physical, and behavioral domains. This in-home sensor technology has been installed in over 200 homes in the Portland, OR (USA) metropolitan area most of which are currently being monitored. As a result, as part of the ISAAC study we have unobtrusively collected millions of gait velocity measurements from over 200 hundred subjects in their own residence during normal daily activities.

In this paper, we discuss a method for longitudinal analysis of these in-home collected gait velocities. We proceed with a brief description of the gait velocity measurement system and data collection followed by a description of a model for the probability density function of these gait velocities including the assumptions underlying this model. We then describe an algorithm for estimating this density function and its evolution over time and provide values for the algorithm parameters that perform well both for abrupt changes and slower changes over time, based on empirical evidence. We follow by demonstrating the proposed method of analysis on two subjects; one who suffered an acute medical event during the monitoring period and one who suffered a slow decline in function over time. Finally, we conclude by discussing extensions of this methodology and future work.

## II. Data Collection, Modeling, and Estimation

In this section, we briefly describe the in-home gait velocity estimation and collection followed by a model for the probability density function of the gait velocity measurements. We then discuss the estimation procedure for the density function and the corresponding evolution over time.

### A. In-home Gait Velocity Data Collection

A detailed description for estimating gait velocity and data collection is described elsewhere [10]. Here we provide a brief description of the procedure for completeness. A sensor line is defined as a linear array of four PIR motion sensors placed on the ceiling with approximately 61 cm (2 ft) between adjacent sensors. The field-of-view of each sensor is restricted to +/− 4 degrees to increase the precision of subject localization and prevent sensor firings unless a subject walks directly under a sensor. In addition, the sensor line placement is chosen to be in the hallway or other narrow corridor to restrict the path the subject walks to be approximately linear with respect to the sensor line.

As a subject walks through the line, the four sensors will fire sequentially giving time information about when the subject is underneath each of the sensors. Since uncertainty exists in both specific location of the subject and time of firing (due to wireless transmission and time-stamping errors), we use a statistical linear model to relate the velocity of a subject to the position and time information from each sensor firing. By assuming that the subject walks with constant velocity through the sensor line, we can use total least squares to estimate the velocity from the model. While in general only three of the four sensors need to fire in order to estimate velocity, in this paper we focus on walking events where all four sensors have fired. Before estimating velocities from the raw sensor data, we prefilter to remove events where the velocity is not approximately constant. This is done by requiring that the time between sensor firings of adjacent sensor pairs in the line normalized by the physical distance between these pairs match each other within a threshold based on the noise tolerance of the sensors. This step prevents making estimates for cases where the walking event does not satisfy the model assumptions (such as when a subject pauses partway through the sensor line during the walking event). The end results is an estimated gait velocity and corresponding time stamp for each time a subject walks though the sensor line.

### B. A Model for Gait Velocities

For the present analysis we model gait velocities as being drawn independently and identically distributed from an underlying unknown but parameterized probability density function. We assume that the parameterization of this density does not change much over short time scales but can vary over longer time scales. In this description we have purposefully not defined short or long time scales as we treat these as user specified parameters in the following subsection on estimating the probability density function. Symbolically, we assume that

$$v_t \tilde{} f(\theta_t) \quad (1)$$

where $v_t$ is the observed velocity at time $t$ governed by the density function $f(\Theta_t)$, which is parameterized by a parameter vector $\Theta_t$ that is also a function of $t$. We also require that

$$f(\theta_t) \approx f(\theta_{t'}) \text{ for } t, t' \in [a, b) \quad (2)$$

for $[a,b)$ some short interval of time. Equation (2) describes the condition on which it is appropriate to use all the data in the interval $[a,b)$ to make estimates of the density at time $t$.

### C. Density Estimation and Evolution

The first step in estimating the underlying gait velocity density is to identify a reasonable density function to model the velocities. While both Gaussian and Gamma families of distributions have been successful at modeling these velocities on an individual basis and have parsimonious parameterizations, we have found that neither type of distribution offers enough flexibility to adequately model the wide variety of empirical distributions that arise from different subjects. As a result, we chose to leave the density function unconstrained and use kernel density estimation on windows of the data. In terms of the model described above, we estimate the underlying distribution at time $t$ as

$$\widehat{f}(v;\theta_t) = \frac{1}{n}\sum_{i=1}^{n} K(v_i - v; h) \quad (3)$$

where $h$ is the bandwidth of the kernel $K$, the parameterization vector $\Theta_t = \{v_{t'};\ \forall t' \in [a,b)\}$ consists of all data in the specified time window denoted by $[a,b)$, and $i$ indexes the $n$

velocities used in the estimate. Selection of the window $[a,b)$ is what defines the short time scale for which we assume the density to be approximately constant.

In addition to estimating the density function for a specified window of the data, $[a,b)$, we also estimate the time $t$ as $\hat{t}$ associated with the density estimate as the average of the corresponding times of all walks occurring in the interval. This step is necessary due to the nature of the data collection step described above. Because we only estimate a velocity when the sensor line detects a walking event, our data set consists of walks that are not equally distributed in time throughout the interval $[a,b)$. As a result, we must also estimate the time at which the density estimate is most representative (specifically, the time that is the average of the estimated velocity timestamps).

In order to track the evolution of the density over time, we repeat equation (3) on new windows of data denoted by $[a_{k+1}, b_{k+1})$. Each new data window is related to the prior window by the relationship

$$[a_{k+1}, b_{k+1}) = [a_k + \alpha w, b_k + \alpha w) \tag{4}$$

where $k$ indexes the data windows, $w$ is the window length and $\alpha$; $0 \leq \alpha < 1$ is an overlap parameter that provides a degree of smoothing to the density estimates by using a portion of the data at the end of the prior interval in the estimate of the density in the next interval. Once density estimates have been made at all the desired time intervals, the entire density function can be interpolated uniformly across the entire time period for which the densities were estimated. This step is desired to fill in locations where the gait velocity data is sparse (and thus there are fewer density estimates), which can occur due to lack of data caused by subject vacations, extended time out of house, or technical reasons.

The steps described above to estimate the gait velocity density function and its evolution require the specification of several parameters. For our implementation on the subjects' data described below, we selected a window length of $w = 60$ days and an overlap parameter $\alpha = 0.25$. We started the first window on the first day of available gait velocity data and indexed through the entire available record of data. We used a Gaussian kernel defined as

$$K(v_i - v; h) = \frac{\exp\left(-(v_i - v)^2 / \left(2h^2\right)\right)}{\sqrt{2\pi}h} \tag{5}$$

with h selected according to Silverman's suggestion [12] as

$$h = \left(\frac{4\hat{\sigma}^5}{3n}\right)^{1/5} \tag{6}$$

We note that (6) describes an estimate of the optimal bandwidth for estimating an underlying Gaussian density. While we did not assume the underlying density was Gaussian, we determined empirically that this bandwidth allowed reasonable density estimates. An excellent and thorough description of bandwidth selection and density estimation that motivated many of our decisions can be found in [12]. In order to prevent poor density estimates in sparse data regions, we also required at least 20 walks in each window to estimate a density. Finally, we used linear interpolation to estimate the density function for each day between the first and last days of available data. Other interpolations can be used if positivity constraints are maintained and the density estimates at each time point are renormalized to make the interpolated functions true densities. We selected these parameters for use in the estimation procedure based on empirical evidence supporting good performance on data from a wide variety of subjects with both abrupt changes and slower changes over time.

## III. Application to Eldercare

In this section we show the results of applying the previously described algorithm to walking speed estimation obtained from the homes of two subjects with interesting data records. These two subjects were chosen from many tracked subjects to illustrate the ability of the system to track the distribution and to detect important changes.

### A. Subject 1

Subject 1, a 91 year old female at the time of enrollment in the ISAAC study, had her home installed with our in-home assessment technology including a sensor line and other technology described elsewhere [13]. She was considered active in the technology arm of the ISAAC study as of November, 2007. The results of applying the previously described algorithm to the gait velocity data from her home are shown in fig. 1.

We discuss two features of interest in fig.1. First, in August of 2008 there is a smearing in the density estimate that was later shown to be the result of a technical issue that caused the data for the month of August to be excluded. As a result, estimates near this time period used fewer data points and thus had a higher variability in the density estimate leading to a smearing of the density estimate in the region of missing data. More importantly is the abrupt decrease of approximately 30 cm/s in the gait velocity density (a shift in the distribution from being centered at 70 cm/s to approximately 40 cm/s) followed by an increase over a few months to a stabilizing central tendency of approximately 55 cm/s. Subject 1 experienced a stroke in November of 2009 and had a partial recovery toward pre-stroke abilities over the next few months. However, at least in terms of gait velocity her pre-stroke ability never fully recovered and she remained at an average walking speed close to 55 cm/s until her death in early 2011. As can be seen in fig.1, the entire cycle of abrupt change in function due to stroke, partial recovery of function and stabilization at a new ability level is plainly shown in the evolution of the gait velocity density function.

### B. Subject 2

Subject 2, a 96 year-old male at the time of enrollment in the ISAAC study had technology installed in his home as described for subject 1 and was considered active in May of 2007. We were able to monitor this subject until he moved from his residence in a retirement community to assisted living in December of 2010. The evolution of his in-home gait velocity density function is shown in fig. 2.

Of particular note in fig. 2 is the slow decline of central tendency in the gait velocity distribution over time. This corresponds to a transition in cognitive function as evidenced by the scores of this subject on the clinical dementia rating scale, or CDR. Specifically, this subject first received a CDR score of 0.5 in 2009, indicating probable mild cognitive impairment (MCI). This MCI diagnosis was confirmed by consensus of a neurologist and other expert clinical personnel. Further, this slow decline in gait velocity over time preceded the subject's move into assisted living thus predicting the future need for advanced care. Both of these phenomena are consistent with the associations between gait and adverse outcomes outlined in the Introduction section.

## IV. Conclusion and Future Work

In this paper we discussed a novel method for analyzing in-home collected gait velocities. In addition to detailing an algorithm to estimate the evolution of gait velocity over time and discussion of algorithm parameters that have worked well over a wide variety of subjects and gait changes, we demonstrated how the methodology of monitoring the evolution in gait velocity over time can identify changes associated with adverse outcomes. Additionally, we demonstrated that this method is applicable for both detecting acute changes in gait function and tracking longer-term changes that occur more slowly over time. We demonstrated this on two subjects who have been tracked for over three years each who both suffered adverse health outcomes that were either detected or predicted by the gait velocity data.

Future work will comprise two parts. First, automatic algorithms will be developed that can generate relevant clinical alerts based on changes in the gait velocity density function. Second, plots such as those shown in figs 1 and 2 should be integrated as part of personal health records for elderly. We believe that this type of visualization tool will aid doctors and caregivers in diagnosis and identifying patients at increased risk of adverse health outcomes.

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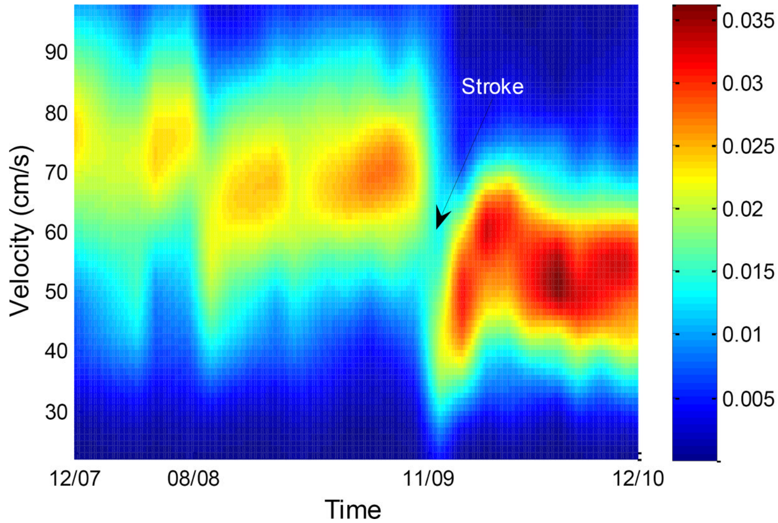


**Fig. 1.**
An estimate of the evolution of the probability density function of gait velocity for subject 1 noting time and effect of the stroke in November of 2009. The density values are represented by the color shown in the colorbar.

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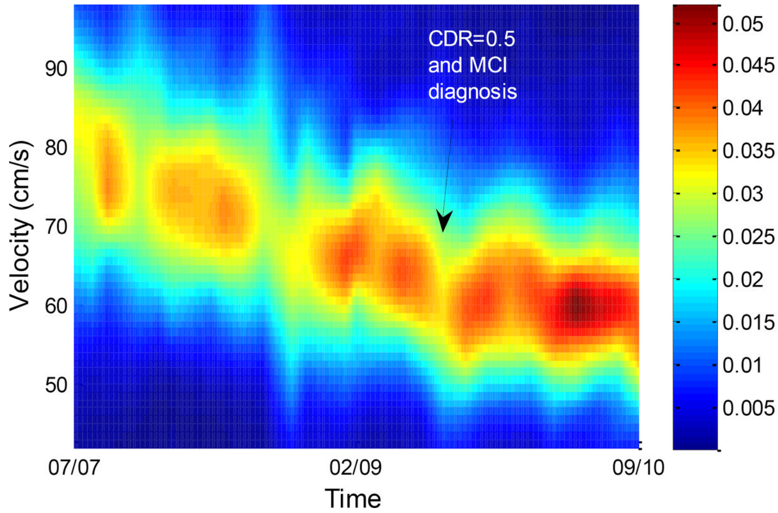


**Fig. 2.**
Estimate of the evolution of the probability density function of subject 2 noting the time of the clinical dementia rating scale score (CDR) and corresponding diagnosis of mild cognitive impairment(MCI). The density values are represented by the color shown in the colorbar.