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Does external walking environment affect gait patterns?

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Abstract—The objective of this work is to develop an understanding of the relationship between mobility metrics obtained outside of the clinic or laboratory and the context of the external environment. Ten subjects walked with an inertial sensor on each shank and a wearable camera around their neck. They were taken on a thirty minute walk in which they mobilized over the following conditions; normal path, busy hallway, rough ground, blind folded and on a hill. Stride time, stride time variability, stance time and peak shank rotation rate during swing were calculated using previously published algorithms. Stride time was significantly different between several of the conditions. Technological advances mean that gait variables can now be captured as patients go about their daily lives. The results of this study show that the external environment has a significant impact on the quality of gait metrics. Thus, context of external walking environment is an important consideration when analyzing ambulatory gait metrics from the unsupervised home and community setting.

I. INTRODUCTION

Falling is a common occurrence in older adults and is a leading cause of serious injury, loss of independence, and nursing-home admission [1]. Prevention of falls results in prevention of injury and maintenance of independent living [2]. It is important to identify elderly persons who are particularly at risk of suffering a fall. Identification of high risk individuals allows fall prevention interventions to be directed appropriately.

Research has shown that metrics from supervised mobility assessments can be used to identify elderly patients who may be at an increased risk of falling. It has been shown that stride time variability from a supervised walking trial can be used to predict risk of falling [3]. More recently it has been shown that wearable sensor metrics from a timed up and go (TUG) test can be used to predict risk of falling [4]. Such tests are very useful because they can identify individuals who are at an increased risk of falling. Such individuals should be directed towards interventions to reduce their risk of falling.

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A limitation of the methods presented above [3, 4] is that these tests require clinical supervision to be performed. With advancing technology it is now possible to use wearable sensors to monitor mobility as people go about their daily lives, without the need for a visit to the hospital or clinic [5]. Utilization of mobility data from daily life to identify falls risk would mean that a much larger group of elderly individuals could have their falls risk monitored compared to using clinically supervised testing alone. An added benefit would be that real world mobility data would be used to assess falls risk, as opposed to mobility data from the controlled supervised clinical environment.

Lesson's learned regarding mobility metrics and their relationship to falls risk from the supervised environment cannot be directly applied to an unsupervised environment. It is not guaranteed that a person will move the same in daily life as they move in a supervised clinical setting.

The main reason for the difference in the quality of mobility patterns between a supervised and an unsupervised environment is the context in which the movement occurs. In a supervised setting, such as a clinic or a laboratory, the external environment is controlled and participants are focused completely on performing a certain motor task. In an unsupervised setting, such as when somebody is walking to the grocery store, the external environment is variable and participants could be moving differently based on challenges in the external environment. These challenges might include things such as a busy walking path or a muddy walking path. However, obtaining knowledge of the external walking environment is difficult. It would not be reasonable to ask a patient to manually annotate each type of environment they walk in as they go about their daily life.

Preliminary research on one patient has outlined how context of walking environment may be obtained using a wearable camera [6]. This research suggests that knowledge of external walking environment (*the context*) provides clinically important information when analysing unsupervised quality of gait information from daily life. The research question posed by such a scenario is to determine if context of walking environment combined with quality of gait metrics predicts falls risk better than having no knowledge of gait context. Proving this would mean that unsupervised gait monitoring in the community using wearable sensors could be used to assess falls risk and identify those individuals most in need of falls prevention training. This research question requires a large, elderly faller based testing group. However, before that is done

preliminary work is required to determine if external walking environment has an impact on quality of gait in control subjects.

The purpose of the present study is to do this and develop an understanding of the relationship between the type of walking environment and quality of gait information from healthy subjects.

II. METHODS

In order to investigate gait metrics in different external walking environments a series of case studies were completed. Enlisted volunteers walked on a range of different terrain while wearing an inertial sensor (Shimmer 3, Dublin, Ireland) on each shank and a wearable camera (Autographer, Oxford, UK) on a lanyard around their neck. Figure 1 shows how the sensors were worn on the subjects.

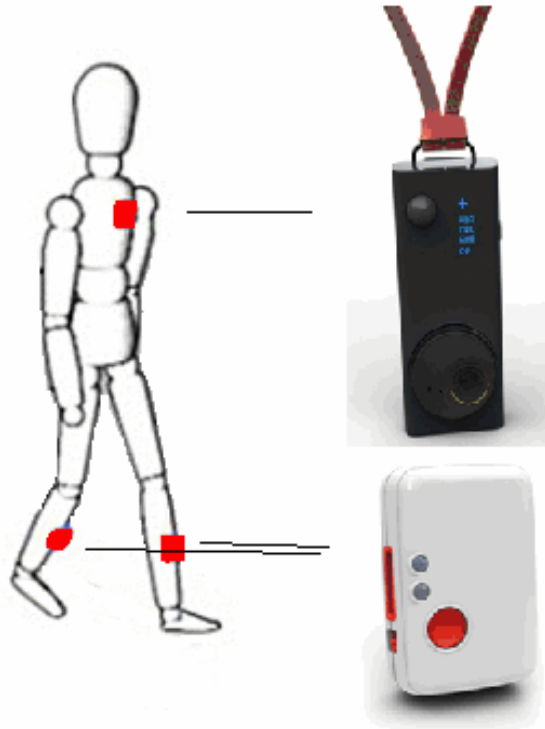


Figure 1. Sensor set up on subjects.

A total of ten subjects were recruited for the study (29.4 years on average, ± 4.7 years). Participants were included if they were not previously diagnosed with any gait or balance disorders. The aims and design of the study were explained to all prospective volunteers verbally and informed consent was obtained prior to data collection. Ethical approval was obtained from the University.

The firmware on the inertial sensors was modified to allow for on board data storage. The accelerometer range on

the accelerometers was set to ± 6 G and they sampled at 102.4 Hz. The gyroscope range was set to ± 1000 deg/s in order to ensure that peak rotation rate values during the swing phase of gait were captured [8]. The inertial sensors were activated at the same time as the camera and recording of data commenced. The inertial sensors were placed just above the lateral malleolus of each ankle joint and were held using custom made semi-elastic Velcro straps. The wearable camera was placed around the neck of the participants with a lanyard.

Participants walked with an experimenter beside them who told them where to go and noted the times. Participants negotiated five different walking terrains: regular walking on a flat surface (normal), a busy hallway, a rough walking surface (gravel), and a hill and blindfolded on a flat surface. No breaks were taken between the different walking conditions. Subjects walked for at least thirty seconds on each terrain to ensure the wearable camera would get a photo. Subjects were instructed to walk at a self-selected normal walking pace. The time the participant commenced and completed each walking condition was noted and later used to identify each walking condition in the inertial sensor data. Following completion of data collection, the inertial sensors and wearable camera were removed from participants and their data uploaded to a computer.

A. Algorithm

A method was used to detect initial contact (IC) and toe-off (TO) from the sagittal plane gyroscope signal that is based on the algorithm presented in Greene et al, [7]. However, since the Greene et al algorithm was developed for people walking in straight lines at different speeds in a controlled environment, it did not work for a small number of steps in which subjects had to make major adjustments to their gait to get around a group of people or get through a very tight area. A problem was occurring with the original algorithm due to the fact that IC points were missed because they were of lower magnitude than threshold five, as outlined in [7]. Another check was added to the algorithm, which only occurred if no minimum was found below the value of threshold five. In these instances, the closest minimum to mid-swing was used that was below 50 deg/sec. A similar check was used to find TO's which were not identified using the steady state feature detection algorithm. Detection of IC and TO in the gyroscope signal allowed for the calculation of stride time, stance time as well as stride time variability. Stride time variability has been shown to be useful in the prediction of falls risk in the elderly [3]. Peak rotation rate of the shank during swing phase was also calculated, using a previously published method [8]. This variable was included because it has been suggested to be related to gait patterns which may lead to joint degeneration over time [8].

B. Data Analysis

Evaluation of the quality of gait under different environmental contexts was achieved by means of analysis of average stride times in each context. Stride time was

defined as the time between each IC on the same foot. A repeated measures ANOVA was used to look for stride time differences between the various external walking environments. Stride time was calculated for each stride for each participant in each context, averaged for each foot, and then averaged between feet for each participant. Variance in each context was also calculated for each participant.

III. RESULTS

A one way repeated measures ANOVA was conducted to compare stride time across each of the walking conditions. Stance time was not included because of its high level of correlation to stride time ($r = 0.915$). Stride time variability and peak shank rotation rate were not included because it is appropriate to use ANOVA on one dependent variable only. The means and standard deviations are presented in Table 1. There was a significant effect for walking environment, Wilks' Lambda=.173, $F(4, 8)=7.160$, $p=.018$, multivariate eta squared=.827.

TABLE I. AVERAGE AND STANDARD DEVIATION (IN BRACKETS) OF GAIT METRICS OVER THE FIVE DIFFERENT WALKING ENVIRONMENTS.

Condition	Stride time	Stride time variability	Stance time	Peak shank rotation rate during swing
Units	Sec		sec	deg / sec
Normal	1.05 (.07)	.001 (.001)	.58 (.05)	391.1 (22.1)
Hill	1.16 (.11)	.012 (.012)	.68 (.08)	360.4 (27.3)
Rough	1.07 (.06)	.002 (.001)	.61 (.04)	395.2 (24.8)
Blind	1.11 (.07)	.002 (.001)	.64 (.04)	363.9 (26.0)
Busy	1.16 (.09)	.010 (.008)	.67 (.07)	340.7 (46.8)

Figure 2 shows examples of photographs from the wearable camera in four of the different walking conditions. The blind-folded walking condition is not shown.



Figure 2. Examples of photographs from the wearable camera in four different walking conditions; A – normal walking, B – walking on a rough surface, C – walking in a busy area and D – walking up a hill.

IV. DISCUSSION

The results from this data collection suggest that the external environmental context in which a walking period occurs can have an effect on gait patterns. With advancing technology, it is now possible to measure gait patterns outside of the lab, as patients go about their daily life. This work indicates that taking into account the context of the external environment is important for such monitoring scenarios, as abnormal walking patterns may be due to changes in the walking environment, not internal changes to the patient.

Previous work has shown that quality of gait metrics from three days of normal activity can identify elderly people at risk of falling as good as clinically based tests [9]. Being able to assess falls risk via wearable sensor use as patients go about their daily life would allow many more patients to be monitored, as opposed to patients only having their falls risk assessed upon a visit to a clinician. While this previous work [9] shows that falls risk can be obtained from gait data from the home and community, there is a possibility that the additional knowledge of the external environment during certain gait events may allow for a more accurate falls risk prediction as well as giving clinicians powerful information to guide rehabilitation programs to reduce the chance of falling.

Previous work has proposed that when obtaining unsupervised gait metrics as a person goes about their daily life it is important to take into consideration the context in which the walking is occurring [6]. This work suggested that the use of a wearable camera would allow for determination of the external environmental context in which a gait period occurs. We controlled the external environmental context in this study, however, from Figure 2, it can clearly be seen that the environment in which the gait pattern occurred can be classified from the wearable camera photographs.

In this preliminary work we have only considered the context of the external walking environment. There are many other important contexts to consider when analyzing mobility data from the home and community setting; such as time of day, attentional focus, syncope and health issues such as blood pressure and heart rate. The ongoing research and development into this wide range of sensor technologies make it likely that insight into these factors could be obtained in the near future

Knowledge of the environmental context in which a walking period occurs may prove a useful tool for clinician's to assess in which types of environments certain patients have difficulty walking. This could be helpful in designing more effective rehabilitation programs as well as tracking the progress made during rehabilitation.

Previous work in the area has utilized a lumbar mounted inertial sensor to obtain gait metrics. In this work, we used a

sensor mounted on each shank. Both mounting scenarios have advantages and disadvantages. A lumbar sensor is more uncomfortable in everyday life, as it can be felt when sitting down. However, two shank sensors mean more hardware is required. Due to the large amount of previous work using shank inertial sensors to monitor gait patterns as well as the fact that shank sensors are not in the way when sitting down we felt that this sensing location was most appropriate.

In this preliminary work, periods of walking were annotated and manually found in the inertial sensor data. For clinical use, walking periods should be automatically detected. Previous work in the area has used either a signal magnitude area threshold based activity detection monitor [10] or used a method based on a threshold of the energy in the frequency domain.

In this study, the external walking environment was controlled. The purpose of this work is to build towards a system that consists of inertial sensors and a wearable camera that can be used to monitor peoples gait patterns and the environment in which walking periods occur as they go about their daily life. The current state of the art wearable camera research to identify external environment is still at the stage of manually annotating image data [11]. Once manual annotation is completed on a large data set, such data could be used with machine learning techniques to develop classifiers which may automatically determine the environment that a person is walking in.

The wearable camera information in this preliminary work was not used to quantify type of walking environment because the researchers brought participants out to walk on a set route that included specific environmental conditions. The use of a wearable camera could allow for quantification of external walking environment when obtaining unsupervised gait information as a patient goes about their daily life.

Stride time variability has been shown to be related to falls risk in the elderly [3], however, this data was collected in a controlled laboratory environment. Now that sensor technology is allowing researchers to collect ambulatory gait information from the home and community setting, there is a need to understand how such knowledge relates to mobility information from an uncontrolled, unsupervised environment. The use of a wearable camera to obtain environmental context is one way to gain a deeper understanding of how mobility information from the home and community setting can be interpreted.

Peak shank rotation rate during swing is a potentially useful variable in detecting abnormal gait patterns because it has been shown to be altered in abnormal gait when temporal variables are not altered [8]. For the healthy subjects in this study, peak shank rotation rate was lower in the busy, blind and hill walking conditions. Such a variable may prove useful in understanding gait information in the home and community setting.

Research should consider if less invasive sensor technologies may be able to be used to provide contextual gait information. GPS data may be able to be used along with information such as, where a person lives and some of their daily habits. However, with the advancement of camera technology - wearable cameras are becoming smaller and more ubiquitous - there is a strong possibility that wearable cameras can be worn without anybody noticing.

The results presented in this paper suggest that the external environmental context in which walking occurs affects a person's gait pattern. This finding means that future work should consider if knowledge of the external environment of gait patterns in the home and community setting can better predict falls risk than without having any knowledge of the external environmental context.

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