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Semi-automated Video-based In-home Fall Risk Assessment

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Abstract. The development of an in-home fall risk assessment tool is under investigation. Several fall risk screening tests such as the Timed-Get-Up-and-Go-test (TGUG) only provide a snapshot taken at a given time and place, where automated in-home fall risk assessment tools can assess the fall risk of a person on a continuous basis. During this study we monitored four older people in their own home for a period of three months and automatically assessed fall risk parameters. We selected a subset of fixed walking sequences from the resulting real-life video for analysis of the time needed to perform these sequences. The results show a significant diurnal and health-related variance in the time needed to cross the same distance. These results also suggest that trends in the transfer time can be detected with the presented system.

Introduction

Falls are one of the major health risks in our rapidly aging population. Approximately one in three people older than 65 fall at least once each year [1]. Falls frequently result in moderate to severe injuries and fear of falling [1], which both can limit the activity of the older person. The mobility and balance of the person that is already at risk therefore further declines. This subsequently increases the risk of future falls [1,2].

An accurate fall risk estimation can be an important aid in the prevention of these fall incidents. When an elevated risk is detected, both therapeutic and preventive actions can be initiated, e.g. installing an exercise and training program to enhance gait and mobility, adapting the medication, etc.

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One of the commonly used screening tools to assess fall risk is the Timed Get-Up-and-Go test (TGUG) [3,4], where the subject is asked to rise from a chair, walk three meters, turn around, return to the chair and sit down. The manually recorded time needed to complete the test, together with the observations of the patient's walking pattern by the clinical staff, are used to estimate the fall risk. The TGUG test, however, is typically administered in a clinical setting, e.g. in the hospital. Studies have shown that due to the test awareness of the person and the unnatural setting the results of the TGUG test are not always representative of the fall risk of a person in his natural home environment [5,6].

Although automating the TGUG test is currently investigated by several research groups [5,7,8], these systems are thus far only used in a simulated environment and therefore do not reduce the effects of the test awareness and the unnatural setting on the test results. They also do not incorporate any additional challenges related to real-life measurements [9].

Our research focuses on the development of an automated in-home fall risk assessment tool which uses real-life data acquired with cameras. The goal of the system is to automatically assess the transfer time, which is a component of the TGUG test, in the home environment on a daily basis. Previous studies have shown that gait speed can be used as one of the factors to predict falls [11,12]. Although the TGUG test provides more information than gait speed because it includes standing, turning, and sitting, in [3] it is shown that the walking speed is one of the components of the TGUG test which is significantly different between people with and without an elevated fall risk. An in-home daily assessment of the transfer time can therefore provide a continuous measure which in turn can provide valuable information for the caregivers.

1. Methods

The presented system measures the time each participant needs to cross a fixed distance between the living room and bathroom based on video data. We opted for these transfers because they frequently occur during the day and are mostly executed in the exact same way. This time is measured several times a day.

1.1. The Participants and the Resulting Dataset

For a period of three to twelve months four camera systems consisting of multiple wall-mounted IP-cameras were installed in the homes of 4 senior citizens. An overview of the demographic characteristics of the four participants can be found in table 1. When multiple walking aids are mentioned the participant alternates between different walking aids. A TGUG test was obtained from each participant before the acquisition period (table 1). Depending on the person one or more TGUG tests were obtained during the study (see table 2).

1.2. The Algorithm

1.2.1. Preprocessing

To facilitate the timing of the walking sequences the video data are processed isolating the participants from their surroundings in the video images. To accomplish this four

Table 1. Demographic characteristics of the test subjects.

Participant	Age	sex	Home	TGUG results	Walking aid	Measured sequences
A	74	m	his own home	11 sec	na*	80
B	75	f	service flat	16 sec	rollator, cane, na*	64
C	95	f	service flat	23 sec	rollator, na*	33
D	95	f	retirement home	+ 20 sec	rollator	34

Notes:
TGUG test obtained before the acquisition period
* na: no walking aid

(a) *Partitioned frame* (b) *Unpartitioned frame*

Figure 1. Frames used for the timing of walking sequences.

image processing steps are performed. First, the foreground is detected using an estimation of the background which is subtracted from each video frame. From the resulting foreground the shadows are removed using a technique of background cross correlation. After this an erosion / dilation step is applied to all the foreground pixels followed by a connected component analysis to detect all foreground objects. A bounding box is subsequently drawn around the largest foreground object, this being the person in the video.

A more detailed explanation of these different steps can be found in [9].

1.2.2. Timing of walking Sequences

To measure the walking time over a fixed track a start and stop point needs to be defined. Two different methods can be used to define these points. The first method consists of the division of each frame into three regions using two predefined borders (figure 1a). The time measurement starts when the test subject crosses the first line and stops when the test subject crosses the second line. The subject is detected as crossing the line when the bottom right corner of the surrounding bounding box, corresponding with the feet of the test subject, crosses the line. The second method uses start and stop events and can be used in situations where the camera position causes the walking distance in view to be too short to create 3 subdivisions (figure 1b). For instance, the opening or closing of a door which causes a sudden change in the dimensions of the bounding box can be used as start or stop points. Start and stop events were used to time the walking sequences of participant A. In this case the time was measured from when the participant walked into the camera view until he started to open the door.

2. Results

First, we measured diurnal variation in transfer time. To evaluate this, 57 walking sequences of participant A were selected during 17 consecutive days. For each of these sequences the duration of the walk was measured.

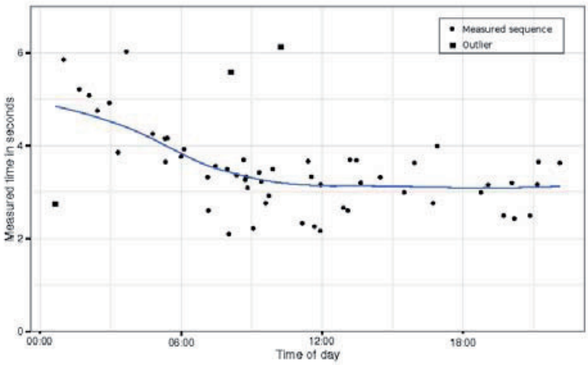

Figure 2. Automatically measured times per walking sequence during a period of 17 days.

During the second analysis the transfer times were measured on the day before the manually recorded TGUG test, during the day of the test and the day after. These times were then compared to the results of the TGUG test. The walking sequences were manually classified per walking aid, therefore the semi-automatically measured times are also classified per walking aid. Transfer times between subjects cannot be compared due to the variation in walking trajectories between participants.

2.1. Transfer Time during the Day

Figure 2 shows the semi-automatically measured times of each walk, performed by participant A, during the first experiment. A local regression model was fitted on the presented data using a sliding window to detect trends in the presented data [10], the resulting model is also shown in figure 2. The time needed to perform the transfer to the toilet before 7 a.m. is higher than after 7 a.m. Figure 2 also shows three outliers. The first outlier was measured during a night when the participant suffered from nausea and diarrhea. The other 2 were measured on the morning following this night time episode.

2.2. Transfer Time compared to the TGUG Test

During the second analysis the semi-automatically measured transfer times were compared to the manually recorded TGUG test. Only measurements between 7 a.m. and 11 p.m. are included in this analysis. Table 2 shows the results measured during the first three months of the project. This table consists of the TGUG test for all participants and the semi-automatically measured transfer times per walking aid. The results are assessed individually per participant.

2.2.1. Participant A

The results of the first TGUG test of participant A are slightly better than the results of the other TGUG tests. But when measuring the first test the clinical staff observed a very unstable gait. During the second and the third TGUG test the gait of the first participant was more stable but he needed more time to complete these tests. The semi-automatically measured times for gait speed remain stable during these three months. This suggests that the fall risk of participant A did not change during the measurement period.

Table 2. Timed-Get-Up-and-Go test (TGUG) and semi-automatically measured results.

Participant	TGUG		No walking aid		Cane		Walker	
	Date	Result	Result	Events	Result	Events	Result	Events
A	29 Oct	11	3.1 ± 0.5	10	na	na	na	na
	26 Nov	14	3.1 ± 0.3	4	na	na	na	na
	4 Jan	13	2.9 ± 0.5	9	na	na	na	na
B	30 Oct	22.3	na	na	5.0 ± 0.9	11	7.6 ± 0.9	9
	26 Nov	27.3	4.2 ± 0.3	4	4.6 ± 0.2	8	8.4	1
	8 Jan	25	5.2 ± 1.1	9	5.9 ± 0.9	11	7.2 ± 1.2	11
C	3 Nov	23	8.7 ± 0.9	3	na	na	11.7 ± 1.1	10
	27 Nov	na	8.7 ± 0.5	3	na	na	11.2 ± 1.5	10
	4 Jan	19	6.2 ± 0.2	2	na	na	10.0 ± 0.6	5
D	26 Oct	+20	na	na	na	na	17.5 ± 3.6	10
	17 Nov	na	na	na	na	na	17.8 ± 5.4	11
	30 Nov	+20	na	na	na	na	10.8 ± 3.1	13

Notes:
Measured times in seconds
Times given in columns 'No walking aid', 'cane' and 'walker' are measured semi-automatically

2.2.2. Participant B

Participant B suffered several minor strokes before and during the data acquisition period. In the days before the second TGUG test she suffered another minor stroke resulting in a loss of strength in her right arm and leg. During the second TGUG test she felt the need to support herself with the furniture surrounding her. This significantly slowed her down and had a negative influence on the result of this TGUG test. Although she felt very insecure during the second TGUG test she did not use the walker on several occasions during the measurement period before and after the second TGUG test.

Participant B needed more time to complete the last TGUG test compared to the first test. This can also be seen when comparing the semi-automatically measured times for gait speed measured in the same period as the first TGUG test and the third TGUG test when the participant is using a cane or not using a walking aid. It can also be seen that the time needed to complete the same trajectory depends on the used walking aid.

2.2.3. Participant C

The third TGUG test of participant C was completed faster than the first TGUG test suggesting a slight decline in the fall risk of participant C. This can also be seen in the semi-automatically measured times.

2.2.4. Participant D

A very abnormal and unstable gait was observed for participant D during the whole measurement period. Although she always used a walker to walk to the bathroom she often needed to take short breaks during the walk. This resulted in very fluctuating semi-automatically measured times for gait speed, which can be seen in the standard deviations of these measurements. Although the semi-automatically measured times in the third measurement period are significantly better than during the first period the large standard deviations do not allow us to conclude that her gait improved.

3. Conclusion

These preliminary results indicate that transfer times can be measured from video sequences. The results show a large diurnal and health-related variance in the time needed to cross the same distance. They can therefore provide valuable additional information to the results of the TGUG test, which is currently still a snapshot. Since the automated system cannot provide automated observations of the gait quality itself, it cannot be used as a replacement of the TGUG test. It may, however, be used to detect trends in the walking speed of a person.

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