Automatic detection of health changes through transfer times of elderly based on statistical process control techniques

Greet Baldewijns[1,2,3], Stijn Luca[4], Tom Croonenborghs[1,5] and Bart Vanrumste[1,2,3]

Abstract*—Gait speed and transfer times are measures of functional ability in elderly. Currently data acquired by systems that measure either gait speed or transfer times in the homes of elderly people require reviewing by health care workers. This reviewing can be a time consuming process. To alleviate this burden statistical process control methods are presented that can automatically detect both positive and negative changes in transfer times. Three SPC techniques tabular CUSUM, standardized CUSUM and EWMA were evaluated on simulated transfer times. After parameter optimization of the methods under evaluation it was concluded that EWMA was the better suited method for the desired application.*

I. INTRODUCTION

Because a decline in gait speed has a predictive value for a broad array of adverse events such as physical functional decline [1], [2], cognitive impairment [3], [4] and fall incidents [3], [4] it is often used as a parameter when monitoring the health of elderly people [1], [2].

Gait speed and transfer times can be continuously monitored by wearable sensors such as accelerometers and gyroscopes [5] or by contactless sensors, such as motion detection systems [6], radar [7] and cameras [8]. Although these systems provide accurate patient measurements, health care workers are forced to review these data for each patient which can be very time consuming. A system that can automatically detect changes in these measurements is therefore needed.

For this automatic change detection three statistical process control (SPC) techniques, tabular CUSUM, standardized CUSUM and EWMA, were evaluated. Simulated datasets, generated based on the properties of real life acquired data, were used to optimize and validate each technique.

In the remainder of the paper, first the different datasets for both training and validation are discussed, followed by a general description of the experimental setup. Subsequently the results are presented and discussed and a general conclusion is provided.

II. RELATED WORK

The monitoring of health-related variables for individual patients using SPC was first suggested by Alemi and Neuhauser in 2004 [9]. Since then SPC techniques have been used for quality monitoring of several hospital performance measures such as post operation infection rates, waiting times or the number of fall incidents [10], [11] among others. The use of SPC techniques for the monitoring of gait quality parameters however is new.

III. DATASETS AND EXPERIMENTAL SETUP

Parameters of the proposed SPC techniques were optimized using a grid search technique. For this purpose two simulated datasets were generated: a training dataset to optimize the SPC parameters for the desired application and a validation dataset. The results obtained after this parameter tuning were compared with those obtained when parameters were chosen according to a rule of tumb [13].

A. The datasets

In [8] real life datasets were acquired trough installation of wall-mounted cameras in the homes of four elderly persons for periods varying from 8 to 12 weeks. From this data it was clear that a log logistic model was a realistic assumption for the transfer times.

Three key aspects were taken into account when generating simulated transfer times. First the location and scale parameters (μ and σ resp.) of the log-logistic distributions from which the simulated transfer times were sampled were determined, based on the in [8] acquired real life data, through maximum likelihood estimation for both a stable and an unstable gait model. A stable gait model was defined with a μ of 1.504 and σ of 0.155. An unstable gait model had a μ of 2.097 and σ of 0.204 (figure 1 shows the real life dataset of the participant with a stable gait pattern and fitted log logistic function). Next the number of measurements per day were determined by sampling a Poisson distribution. Lastly linear interpolation was used to calculate intermediate model parameters for each day in the transition period when transitioning from a stable to unstable model and vice versa. Four basic simulation scenario's were defined: a scenario for which the gait pattern remains stable during the whole measurement period, one where the gait pattern remains unstable, one where the gait pattern is stable for several weeks at the beginning of the measurement period and transitions during four weeks to an unstable pattern and vice versa. Although we are aware that shorter (for instance after an acute event) and longer transition periods are possible the length of this transition period was again based on the in [8] acquired data

Each basic scenario was generated 20 times for the training set, resulting in a trainings set consisting of 80 simulation sets. For the validation set the basic scenarios were again generated

[1]KU Leuven Technology Campus Geel, AdvISe, Belgium
[2]KU Leuven, ESAT-STADIUS, Belgium
[3]iMinds Medical Information Technology department, Belgium
[4]KU Leuven, Faculty of Engineering Technology, Belgium
[5]KU Leuven, Department of Computer Science, DTAI, Belgium

** © The article that you will start to read is a preprint presented at 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2015 (EMBC). The final publication is available at http://ieeexplore.ieee.org/ DOI: 10.1109/EMBC.2015.7319525

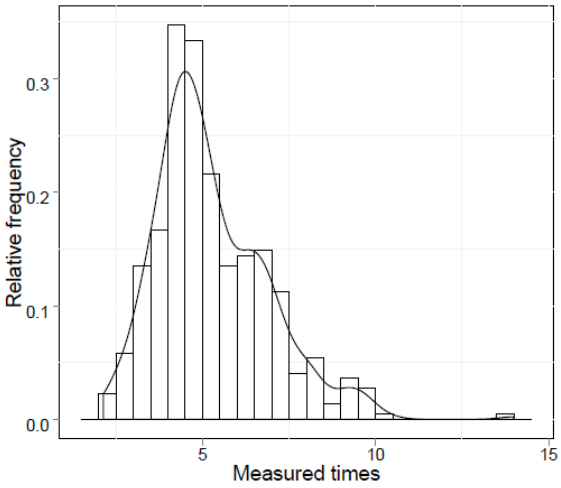

Fig. 1. Histogram of real life measured transfer times of a participant with a stable gait pattern and fitted log logistic function

20 times, again resulting in a validation set consisting of 80 simulation sets.

Since the distribution of the transfer times is skewed a median was calculated for each day. These medians are used as input for the control charts.

B. Experimental setup

1) Statistical process control techniques: In the presented study several control charts were evaluated that are widely known in the area of SPC [13]. These control charts aim to detect trends in the performance of a process and can trigger an alert when variations, not inherent to the process, occur.

There are a multitude of different types of control charts available. However since the evaluated control charts should be able to detect small shifts in the data and should perform well with skewed distributed data the study focussed on the Cumulative sum (CUSUM) chart and the Exponentially weighted moving average (EWMA) chart [13].

CUSUM charts calculate the cumulative sum of the deviations of the transfer times from the target value. The deviations above the target value are accumulated in the positive CUSUM whereas the deviations below the target value are accumulated in the negative CUSUM. Using this method both the information contained in the current point and contained in the previous points are taken into account, therefore facilitating the detection of smaller shifts.

The literature differentiates between Tabular CUSUM and Standardized CUSUM. With the tabular CUSUM the positive and negative CUSUM values are calculated using formulas as

$$C_i^+ = max[0, x_i - (\mu_0 + K) + C_{(i-1)}^+] \tag{1}$$

and

$$C_i^- = max[0, (\mu_0 - K) - x_i + C_{(i-1)}^-] \tag{2}$$

In both formulas μ_0 is defined as the target value. K is referred to as the allowance or the slack value of μ_0 and is expressed in terms of the standard deviation σ of the data:

$$K = \frac{k}{2}\sigma \tag{3}$$

As seen in formulas (1) and (2) both positive and negative CUSUMs accumulate deviations from the target value that are greater than K. Both quantities are reset to zero when they become negative. An alarm is triggered if either exceed the Upper Control Limit (UCL) or Lower Control Limit (LCL):

$$UCL = LCL = h\sigma \tag{4}$$

Both h and k are the parameters to optimize for an effective detection.

Standardized CUSUM uses similar formulas to those of the tabular CUSUM chart. The current measurement however is standardized first using formula

$$y_i = \frac{x_i - \mu_0}{\sigma} \tag{5}$$

. After this standardization a tabular CUSUM chart can be applied on these standardized values.

The Exponentially weighted moving average (EWMA) control chart, is often presented as an alternative to the CUSUM chart when interested in detecting small shifts [13]. It accumulates the exponentially weighted moving average of all prior sample means. The exponentially weighted moving average is calculated as:

$$z_i = \lambda x_i + (1 - \lambda) z_{(i-1)} \tag{6}$$

with λ the weighing factor chosen between 0 and 1. The starting value of z_0 is chosen the same as the central value μ_0.

Upper and lower control limit are calculated as:

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{2-\lambda}[1 - (1-\lambda)^{2i}]} \tag{7}$$

and

$$LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{2-\lambda}[1 - (1-\lambda)^{2i}]} \tag{8}$$

with L determining the width of the control limits. Both L and λ are the parameters to optimize for an effective detection.

An important task for both types of control charts was to find the range of natural variation in the transfer times. To determine this range an initialisation period of 14 days was defined. The mean of the measurements conducted in this period was used as the target value or the central line of the control chart and the standard deviation was used to define the Upper and Lower Control Limit using (4), (7) and (8).

2) Evaluation criteria: To assess the results of the different control charts three evaluation criteria were chosen. They were averaged over multiple scenarios of simulation data of the same type (e.g. the results of all the scenarios which contain a stable to unstable transition are averaged). These criteria are:

TABLE I
INITIAL AND OPTIMIZED CONTROL CHART PARAMETERS

	Tabular CUSUM		Standardized CUSUM		EWMA	
	Init	Opt	Init	Opt	Init	Opt
h	3.00	3.00	3.00	2.96		
k	0.50	0.92	0.50	1.00		
L					3.00	2.92
λ					0.15	0.04

1) Detection Rate (DR)
The detection rate is the percentage of the detected transitions from both a stable to an unstable gait pattern and vice versa. As an undetected transition can have serious medical consequences the detection rate is therefore deemed the most important parameter.
2) Average Run Length
The Average Run Length (ARL) is the number of days needed to detect a transition. This time needs to be kept as short as possible to enable health care workers to respond quickly to changes in transfer times.
3) Average number of false alerts per week(FP)
This is the number of alerts triggered when there is no transition ongoing.

An alert is triggered when the calculated sample statistic, either the positive/negative CUSUM value or the EWMA value, are outside the control limits for at least 2 consecutive days. This is in line with the Western Electric rules, a set of decision rules used for the detection of out-of-control conditions on control charts [12]. An alert is deemed a correct detection if it occurs during or after the transition period. An alert is classified as a false alert if it presents itself at least two days prior to the transition period. If first sample is outside the control limits on the day prior to the transition period and on the second sample is still outside the control limits on the first day of the transition period this is however classified as a correct detection.

3) Optimization of the SPC parameters:
The initial control chart parameters for both CUSUM charts and EWMA were chosen based on a rule of thumb [13]. To improve the results these parameters were further optimized in a grid search for each control chart type individually by maximizing:

$$O = 0.5 \times DR + 0.4 \times ARL + 0.1 \times FP \tag{9}$$

with

- O = optimization parameter
- DR = normalized detection rate
- ARL = normalized average run length
- FP = normalized false positive rate

as a function of the control chart parameters. Tabel I gives an overview of the initial and optimized control chart parameters.

IV. RESULTS

Table II presents the results of our analysis when the parameter choice was first based on a rule of thumb, as well as the optimized and validation results.

A considerably longer ARL is present in the results of the standardized CUSUM chart as compared to those of the tabular CUSUM and EWMA control charts. Although the overall detection rate of standardized CUSUM is slightly higher than the detection rate of the tabular CUSUM control chart the average number of false alerts per week of the standerdized CUSUM chart is 3 times higher than that of the tabular CUSUM chart. This longer ARL and high number of false alerts per week make the standerdized CUSUM chart less suitable than the tabular CUSUM chart.

Although the average number of false alerts per week and the ARL from the EWMA chart are similar to those of the tabular CUSUM chart the overall detection rate of the EWMA chart is notably higher than the detection rate of the tabular CUSUM chart. The EWMA chart is therefore the most suited for this application.

V. DISCUSSION

This study reports on the performance of the tabular CUSUM, standardized CUSUM and EWMA control charts to automatically detect changes in the health of older adults using transfer times. The best performing method was the EWMA control chart. After optimization the selected method had an average detection rate of 82% and an average run length of 9.64 days with the transition period of 28 days. Both results were obtained using the validation dataset. Confirming the suitability of the presented method for the desired application.

However from the results obtained through validation it can be seen that small number of transitions remain undetected and on average one false alert is triggered every 20 days. If the control limits are widened, the number of false alerts would decrease. This would however elongate the ARL and possibly decrease the detection rate. Similarly when the control limits are tightened the opposite happens. Furthermore since a false alert is triggered when the measurements of two subsequent days are substantially different to those of the previous days it could indicate that some health problem is apparent during those days. A compromise was therefore sought between detection rate, ARL and false alerts.

Also, when a person has a very stable gait only small variations in the measured transfer times will occur. The UCL and LCL will therefore ly close together causing the average number of false alerts to rise. Worse when a person has a very unstable gait and thus a wide variation in transfer times important negative variations may remain unnoticed as the UCL and LCL will ly further from each other..

The previously mentioned shortcomings could however be countered by applying more of the Western Electric zoning rules. These rules describe when an alarm should be triggered even though a point lies between the control limits depending on the distance to the central value and the location of the previous points. UCL and LCL can therefore ly further away from each other reducing the number of false alerts but still detecting possible changes in transfer times.

The major strength of the presented method is that it is a generic method. Although the in this paper presented research

TABLE II

RESULTS FROM TABULAR CUSUM, STANDARDIZED CUSUM AND EWMA USING INITIAL PARAMETERS ON THE TRAINING DATASET AND OPTIMIZED PARAMETERS FOR BOTH TRAINING AND VALIDATION DATASETS

	TCi[a]		TCo[b]		TCv[c]		SCi[d]		SCo[e]		SCv[f]		Ei[g]		Eo[h]		Ev[i]	
Detection Rate																		
HU	10%		35%		35%		40%		65%		55%		85%		90%		70%	
UH	70%		100%		95%		70%		95%		75%		90%		100%		95%	
Average Run Length																		
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
SU[j]	2.50	2.12	2.14	1.86	1.86	2.67	6.38	4.34	5.85	4.83	8.27	4.61	2.94	2.36	3.56	2.50	3.07	3.05
US[k]	5.29	5.38	9.20	11.37	12.21	9.50	17.21	13.30	16.89	8.11	23.80	14.07	12.017	5.98	12.30	8.84	16.21	9.76
Number of false alerts per week																		
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
S[l]	0.01	0.04	0.00	0.00	0.01	0.02	0.19	0.16	0.23	0.14	0.27	0.30	0.00	0.00	0.00	0.00	0.00	0.00
U[m]	0.06	0.08	0.01	0.03	0.03	0.04	0.13	0.11	0.07	0.08	0.09	0.13	0.00	0.00	0.01	0.04	0.01	0.05
SU	0.10	0.05	0.06	0.05	0.04	0.04	0.15	0.12	0.18	0.13	0.16	0.12	0.02	0.04	0.01	0.03	0.01	0.02
US	0.05	0.06	0.01	0.04	0.01	0.02	0.08	0.10	0.08	0.12	0.04	0.53	0.00	0.02	0.00	0.02	0.04	0.01

Notes

[a] Tabular CUSUM results on the training dataset using parameters as suggested in the literature

[b] Tabular CUSUM results on the training dataset using optimized parameters

[c] Tabular CUSUM results on the validation dataset using optimized parameters

[d] Standardized CUSUM results on the training dataset using parameters as suggested in the literature

[e] Standardized CUSUM results on the training dataset using optimized parameters

[f] Standardized CUSUM results on the validation dataset using optimized parameters

[g] EWMA results on the training dataset using parameters as suggested in the literature

[h] EWMA results on the training dataset using optimized parameters

[i] EWMA results on the validation dataset using optimized parameters

[j] The gait pattern is stable at the beginning of the measurement period and transitions to an unstable pattern

[k] The gait pattern is unstable at the beginning of the measurement period and transitions to an stable pattern

[l] The gait pattern is Stable during the whole measurement period

[m] The gait pattern is Unstable during the whole measurement period

used transfer times as gait measure it could be applied to gait speed or other quality characteristics as well. A new optimization phase will be necessary to find the optimal values for both λ and L.

VI. FUTURE WORK

Further research will include the validation of the results on real life data and assessing the effects of a change in transition period length on the presented results. Moreover, as it is possible that two trends present themselves subsequently in the transfer times improvements will be made to the control charts to enable the detection of subsequent trends in the transfer times.

ACKNOWLEDGMENT

This work was funded through the ingenieurs@WZC project which was funded by 'Provincie Vlaams-Brabant'. Project partners are OCMW Leuven, KU Leuven, AdvISe and InnovAGE. The authors would like to acknowledge the following projects: iMinds FallRisk project, IWT-ERASME AMACS project, IWT Tetra Fallcam project, ICT cost action AAAPELE and the ProFouND network.

REFERENCES

[1] L.J. Viccaro, S. Perera and S.A. Studenski, *Is Timed Up and Go better than gait speed in predicting health, function and falls in older adults?* Journal of the American Geriatrics Society, 59, (2011), 887-892.

[2] N.M. Peel, S.S. Kuys and K. Klein, *Gait speed as a measure in geriatric assessment in clinical settings: a systematic review*, The Journal of Gerontology: Biological Sciences and Medical Sciences, 68(1), (2012), 39-46.

[3] I. Bautmans, B. Jansen, B. Van Keymolen and T. Mets, *Reliability and clinical correlates of 3D-accelerometry based gait analysis outcomes according to age and fall-risk*, Gait and Posture, 33, (2011), 366-372.

[4] M.E. Taylor, M.M. Ketels, K. Delbare, S.R. Lord, A.S. Mikolaizak and J.C.T. Close, *Gait impairment and falls in cognitively impaired older adults: an explanatory model of sensorimotor and neuropsychological mediators*, Age and Ageing, 41, (2012), 665-669.

[5] S. Hagler, D. Austin, T.L. Hayes, J. Kaye and M. Pavel, *Unobtrusive and ubiquitous in-home monitoring: a methodology for continuous assessment of gait velocity in elders*, IEEE Transactions on Biomedical Engineering, 57(4), (2010), 813-820.

[6] T.L. Hayes, S. Hagler, D. Austin, J. Kaye and M. Pavel, *Unobtrusive assessment of walking speed in the home using inexpensive PIR sensors*, Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE, (2009), 7248-7251.

[7] C.E. Phillips, J. Keller, M. Popescu, M. Skubic, M.J. Rantz, P.E. Cuddihy and T. Yardibi, *Radar walk detection in the apartments of elderly*, Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE, (2012), 5863-5866.

[8] G. Baldewijns, G. Debard, M. Mertens, E. Devriendt, K. Milisen, J. Tournoy, T. Croonenborghs and B. Vanrumste, *Semi-automated Video-based In-home Fall Risk Assessment*, Association for the Advancement of Assistive Technology in Europe (AAATE 2013), (2013)

[9] F. Alemi and D. Neuhauser, *Time-Between Control Charts for Monitoring Asthma Attacks*, Joint Commission Journal on Quality and Patient Safety 2, (2004), 95-102.

[10] K.Y. Lee and C. McGreevey, *Using Control Charts to Assess Performance Measurement Data*, Journal on Quality Improvement 28, (2003), 90-101.

[11] J.C. Benneyan, R.C. Lloyd and P.E. Plsek, *Statistical Process Control as a Tool for Research and Healthcare Improvement* Quality and Safety in Health Care 12, (2003), 458-464.

[12] D. Noskievicova, *Complex Control Chart Interpretation*, International Journal of Engineering Business Management vol5:13, (2013)
[13] D.C. Montgomery, *Introduction to Statistical Process Control*, John Wiley & Sons, 6th edition, (2009), 399-432.