Automatic detection of health changes using statistical process control techniques on measured transfer times of elderly

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***Abstract*— It has been shown that gait speed and transfer times are good measures of functional ability in elderly. However, data currently acquired by systems that measure either gait speed or transfer times in the homes of elderly people require manual reviewing by healthcare workers. This reviewing process is time-consuming. To alleviate this burden, this paper proposes the use of statistical process control methods to automatically detect both positive and negative changes in transfer times. Three SPC techniques: tabular CUSUM, standardized CUSUM and EWMA, known for their ability to detect small shifts in the data, are evaluated on simulated transfer times. This analysis shows that EWMA is the best-suited method with a detection accuracy of 82% and an average detection time of 9.64 days.**

I. INTRODUCTION

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 therefore 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 measurements, healthcare workers still need to review these measurements for each patient individually which is very time-consuming. There is hence a high need for a system that can automatically detect changes in these measurements.

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.

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]. However the use of SPC techniques for the monitoring of gait quality parameters is new.

The remainder of the paper is organized as follows. The different datasets, for both training and validation, and the experimental setup are described in Section II. Section III presents the results followed by a discussion and general conclusion in Sections IV and V.

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II. DATASETS AND EXPERIMENTAL SETUP

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 thumb [13].

A. The datasets

In [8], real-life datasets were acquired from wall-mounted cameras in the homes of four elderly persons for periods varying from 8 to 12 weeks. Analysis of this data shows that a log-logistic model of which the probability density function (pdf) is given by

$$p(x|\mu,\sigma) = \frac{1}{\sigma}\frac{1}{x}\frac{e^z}{(1+e^z)^2}; x \geq 0 \quad (1)$$

$$z = \frac{log(x) - \mu}{\sigma} \quad (2)$$

with

- μ = the location parameter
- σ = the scale parameter
- x = transfer time

was a realistic assumption for a generative model of transfer times and that a Poisson distribution is a good model for the number of measurements per day.

Three key aspects were taken into account when generating simulated transfer times: the parameters of the log-logistic model, the mean of the Poisson distribution and the parameters during the transaction period. First, the location and scale parameters (μ and σ resp.) of the log-logistic distributions were determined through maximum likelihood estimation for both a stable and an unstable gait using the real-life data acquired in [8]. This resulted in a stable gait model with a μ of 1.504 and σ of 0.155 and an unstable gait model with a μ of 2.097 and σ of 0.204. Figure 1 shows the probability density function of a person with a stable gait pattern and of a person with an unstable gait pattern). Next, the number of measurements per day were determined by sampling a Poisson distribution with a mean of 5 measurements a day. Lastly, linear interpolation was used to calculate intermediate log-logistic model parameters for each day in the transition period when transitioning from a stable to unstable model and vice versa. Four basic simulation scenarios were defined for validating the detection

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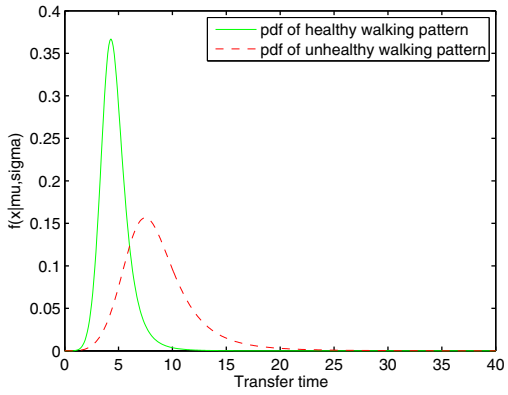


Fig. 1. Probability density function for both healthy (location parameter μ=1.504 and scale parameter σ=0.155) and unhealthy walking patterns (location parameter μ=2.097 and scale parameter σ=0.204)

of changes in health: 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 one where the gait pattern is unstable for several weeks at the beginning of the measurement period and transitions during four weeks to stable pattern. 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 training set consisting of 80 simulation sets. For the validation set the basic scenarios were again generated 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 widely known control charts in the area of SPC [13] were evaluated. 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. This study selected the Cumulative Sum (CUSUM) chart and the Exponentially Weighted Moving Average (EWMA) chart [13] since they are able to detect small shifts in the data and perform well with skewed data distributions.

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 the following formulas:

$$C_i^+ = max[0, x_i - (\mu_0 + K) + C_{(i-1)}^+] \quad (3)$$

$$C_i^- = max[0, (\mu_0 - K) - x_i + C_{(i-1)}^-] \quad (4)$$

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:

$$K = \frac{k}{2}\sigma \quad (5)$$

As seen in formulas (3) and (4), both positive and negative CUSUMs accumulate deviations from the target value that are greater than K. A higher value of K will therefore allow a higher variability in the data. Both positive and negative CUSUM are reset to zero when they become negative. An alarm is triggered if either the Upper Control Limit (UCL) or the Lower Control Limit (LCL) is exceeded:

$$UCL = LCL = h\sigma \quad (6)$$

Both h and k are parameters that can be optimized for an effective detection.

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

$$y_i = \frac{x_i - \mu_0}{\sigma} \quad (7)$$

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:

$$z_i = \lambda x_i + (1 - \lambda) z_{(i-1)} \quad (8)$$

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:

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{2-\lambda}[1 - (1-\lambda)^{2i}]} \quad (9)$$

and

$$LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{2-\lambda}[1 - (1-\lambda)^{2i}]} \quad (10)$$

with L determining the width of the control limits. Both L and λ are 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 initialization 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 (6), (9) and (10).

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:

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 criterium.
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 healthcare 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.

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:

$$O = 0.5 \times DR + 0.4 \times ARL + 0.1 \times FP \qquad (11)$$

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. The different weights correspond to the relative importance of each evaluation criterium as previously discussed. Table I gives an overview of the initial and optimized control chart parameters.

III. 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.

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

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 standardized 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 standardized 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.

IV. DISCUSSION

This study reports on the performance of the tabular CUSUM, standardized CUSUM and EWMA control charts to automatically detect changes in the health condition 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 a transition period of 28 days. Both results were obtained using the validation dataset, confirming the suitability of the presented method for the application at hand.

However, from the results obtained through validation it can be seen that a small number of transitions remain undetected and that on average a 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 one has to note that in this validation an alert is considered false when it is triggered during a non-transient phase but since an alert is triggered when the measurements of two subsequent days are substantially different to those of the preceding 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.

The number of false alerts and the detection rate are furthermore dependent on the stability of the gait during the initialization period. When a person has a very stable gait, the UCL and LCL will lie close together causing the average number of false alerts to rise. When a person has a

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

Transition	Tabular CUSUM						Standardized CUSUM						EWMA					
	Training				Validation		Training				Validation		Training				Validation	
	Default parameters		Optimized parameters		Optimized parameters		Default parameters		Optimized parameters		Optimized parameters		Default parameters		Optimized parameters		Optimized parameters	
Detection Rate																		
Stable→Unstable	10%		35%		35%		40%		65%		55%		85%		90%		70%	
Unstable→Stable	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
Stable→Unstable	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
Unstable→Stable	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
Stable (no transition)	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
Unstable(no transition)	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
Stable→Unstable	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
Stable→Unstable	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

very unstable gait and thus a wide variation in transfer times, important negative variations may remain unnoticed as the UCL and LCL will lie further from each other.

The previously mentioned shortcomings could however be countered by applying more of the Western Electric zoning rules [12]. 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 lie 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 used transfer times as gait measure, it could be applied to gait speed or other quality characteristics as well. A new optimization phase will however be necessary to find the optimal values for both λ and L.

V. 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.

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