Disease State Fingerprint for Fall Risk Assessment

Heidi Similä, and Milla Immonen

Abstract— **Fall prevention is an important and complex multifactorial challenge, since one third of people over 65 years old fall at least once every year. A novel application of Disease State Fingerprint (DSF) algorithm is presented for holistic visualization of fall risk factors and identifying persons with falls history or decreased level of physical functioning based on fall risk assessment data. The algorithm is tested with data from 42 older adults, that went through a comprehensive fall risk assessment. Within the study population the Activities-specific Balance Confidence (ABC) scale score, Berg Balance Scale (BBS) score and the number of drugs in use were the three most relevant variables, that differed between the fallers and non-fallers. This study showed that the DSF visualization is beneficial in inspection of an individual's significant fall risk factors, since people have problems in different areas and one single assessment scale is not enough to expose all the people at risk.**

I. Introduction

One third of people over 65 years old fall at least once each year [1] and the number of falls per year increases with age and frailty level [2]. Furthermore, the world's population is ageing with speed and the number of people aged 65 or older is expected to grow from an estimated 524 million in 2010 to nearly 1.5 billion in 2050 [3]. Falls have serious consequences, because they cause mortality, morbidity, reduced functioning, and premature nursing home admission [4]. Hip fracture is one of the most time and money consuming, quality of life changing consequences of falls. For example during the years 1996–2008 in Finland (population 5 million) approximately 7000 hip fractures occurred per year. The care expenses and consequential expenses are very high after a hip fracture and the quality of life of fallers dramatically drop after an injuring fall. The cost of the first year after the hip-fracture was 14 400€ in 2003 in Finland. If the patient needed to move from home into institutional care after the fracture, the cost for the care was 35 700€ for the first year [5]. Society and individuals need to take preventive actions against falls. Falls can be prevented with interventions targeting multiple risk factors or taking a more specific approach, such as combined muscle strength and balance training [6].

There are several intrinsic and extrinsic factors contributing to a person's fall risk, e.g. balance ability, muscle strength, dizziness, posture, gait, drugs, environmental and cognitive impairment, medical factors, poor footwear, etc. All of these can be seen as individual risk factors. However, it is hard to find a single risk factor that is a cause of a fall and it is unlikely that one assessment measure would have excellent accuracy to predict falls [7]. More commonly there are several simultaneous factors behind the fall.

Even with a comprehensive fall risk assessment that incorporates several scales it is not easy to form a detailed overview of a person's health status and prevailing fall risk factors. As Perell et al. point out in their analytic review of fall risk assessment scales [8], the clinicians have difficulties in selecting the most appropriate assessment scale or they lack knowledge of them. They list the assessment scales with diagnostic abilities from separate studies. However, it doesn't provide information of the scales' reliability and validity within the same subjects. Different scales with same subjects were compared e.g. in [9] and [10] in which a logistic regression models were derived with most predictive variables from several scales.

This paper presents a novel application of Disease State Fingerprint (DSF) algorithm [11] to a holistic visualization of fall risk factors. It allows identification of particular areas with needs for improvement on an individual level as well as comparison of groups with different characteristics, such as people with falls history and people with no falls. The fingerprint visualization can also be used to determine which assessment scales or fall risk factors are significant for the person or population in question. In addition, the DSF is used as a supervised classifier to identify persons at risk based on their data. The algorithm is tested with fall risk assessment data from 42 older adults.

II. Methods

A. Data collection

An extensive fall risk assessment is performed for 42 older adults in two locations in Finland. 27 test subjects are recruited among residents of a senior house in Tampere. Residents apply for an apartment by themselves and are in relatively good economic position. Their background and work history varies a lot, thus they are well representative of the population of interest. All the residents have free access to gym, which may have an effect on their initial physical condition. The participants are recruited to the study by the senior house's service counselor. Furthermore, 15 subjects are recruited in Oulu from a physical exercise group led by a physiotherapist in a local seniors' gym. The inclusion criteria for the study are age 64 years or more, living independently,

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H. Similä, and M. Immonen are with VTT Technical Research Centre of Finland, PL 1000, 02044 VTT, Finland (phone: +35820722111; fax: +358207227001; e-mail: heidi.simila@vtt.fi, milla.immonen@vtt.fi).

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don't have cognitive incapability and is able to perform simple physical exercises independently. Person is excluded from the study if he/she is wheelchair or bed bound or has a medical condition or functionality deficit that prevent from doing simple physical exercises. The participants are recruited on voluntary basis and result with 42 subjects; one male and 41 females. This study was approved by the local Ethics Committee of Human Sciences.

The fall risk assessment consist of following parts: 1) background questionnaire, 2) interview, 3) balance platform assessment with Kinect recording, 4) physical balance and walk tests with an activity monitor, and 5) muscle strength measurements.

Before the tests the participants are given an information sheet about the study and they receive a background questionnaire they fill in beforehand at home. The questionnaire asks about age, gender, height, weight, falls during last 12 months, self-rated balance, incontinence, medication usage, physical activity and it includes scales Activities-specific Balance Confidence (ABC) [12] and Geriatric Depression Scale (GDS) [13].

The participants signed an informed consent when coming to the interview carried out by a researcher. The interview is based on the IKINÄ report [12] and its purpose was to enquire those aspects of fall risk that were not included in the background questionnaire, such as questions about sensory functions and Mini-Mental State Examination (MMSE) [15]. In addition, there were questions about nutrition, alcohol consumption, motivators and barriers for physical exercise, daily behavior, and own evaluation of fall related environmental hazards. After the interview standing balance is tested on a balance platform (Balance Trainer BT4, HURLabs, http://www.hurlabs.com) following the protocol of the Romberg test, i.e. first the person stands 30s with eyes open on the balance platform and then repeats the same with eyes closed. The balance platform has four force sensitive sensors in each of its corner and it incorporates calculation of several parameters such as Romberg quotient, trace length of sway, velocity and area of movement, etc. A depth camera (Microsoft Kinect, www.microsoft.com) is placed about three meters behind and orthogonally to the balance platform in order to study whether it can be used to detect possible sway during the standing tests.

Physical balance and walk tests are led by a physiotherapist in Tampere and by a physiotherapy student in Oulu. The tests include Berg Balance Scale (BBS) [16], Timed Up and Go –test (TUG) [17], five times sit to stand test (STS-5), i.e. time it takes to perform five repetitions, and corridor walking, which includes 4m walking speed assessment. The walk test is performed twice in a corridor of over 20 meters long. During the balance and walk tests the test subjects wore two accelerometers (GCDC X16-2, www.gcdataconcepts.com), one at the lower back near the center of mass and the other in front at the waist level. The sensors were attached with special belts that were adjustable to each person's circumference. A researcher annotated the acceleration measurement by marking each test and subtask with a computer that was synchronized with the accelerometers. The data produced by the accelerometers are used for more detailed movement analysis later on.

In Tampere the lower body muscle strength was measured with gym equipment and HUR performance recorder. The performance recorder is attached to the gym device, where it measures maximum force produced by the user. The specific muscles are leg adductor/abductor and extensor/flexor. After a few minutes warm up with a stationary bike, maximum force produced by each of the four muscles is measured three times. The maximum value is taken into account. In Oulu the same maximum force test was not possible due to available gym equipment. Thus the lower body muscle strength is measured without performance recorder as repetition test [18]. The aim was to find a load (in kilograms) for each muscle, so that the subject is able to perform 3-5 repetitions with the gym device. The devices are the same as in Tampere, i.e. leg adductor/abductor and extensor/flexor. The maximum force can then be estimated according to [19]. The upper body muscle strength was measured by grip strength test with the same hydraulic hand dynamometer by all the subjects. The test was performed three times with both hands and the best result was taken into account. The muscle strength tests were supervised by a researcher or a physiotherapy student. After the whole fall risk evaluation all the participants were given a feedback sheet with main results and interpretation based on their age group averages.

The following table summarizes the main characteristics of the test subjects.

TABLE I. SAMPLE CHARACTERISTICS AND GROUPS

N	Age [years] *(Mean±std)*	*BBS score* *(Mean±std)*	**Grouping methods**			
			Fall Incidents		***ABC Total score***[a]	
			Yes	***No***	***< 80%***	***≥80%***
42	64-85 (74,17±5,57)	34-56 (53±3.64)	11	31	7	35

a. ABC groups divided according to [20], where ABC functional rating was as follows: ABC <50% means poor, <80% moderate and ≥80 % good functional capabilities.

B. Data analysis

The Disease State Fingerprint (DSF) visualization and its underlying Disease State Index (DSI) methods developed by Mattila et al. [11] were applied to the data. The input data to the DSF algorithm should have two classes, e.g. fallers and non-fallers. The feature data is organized as a tree with selected number of leaves under the root. The provided DSI value indicates the proportion of data matching to the profile of positive cases in the model. In the case with fallers vs. non-fallers the positive case means a faller. The DSI values are used for creating a tree visualization of the analysis results, where nodes' sizes show the relative relevance of each feature and colors indicate similarity to the positive (red) and control (blue) classes. More detailed explanation of the algorithm can be found in [11].

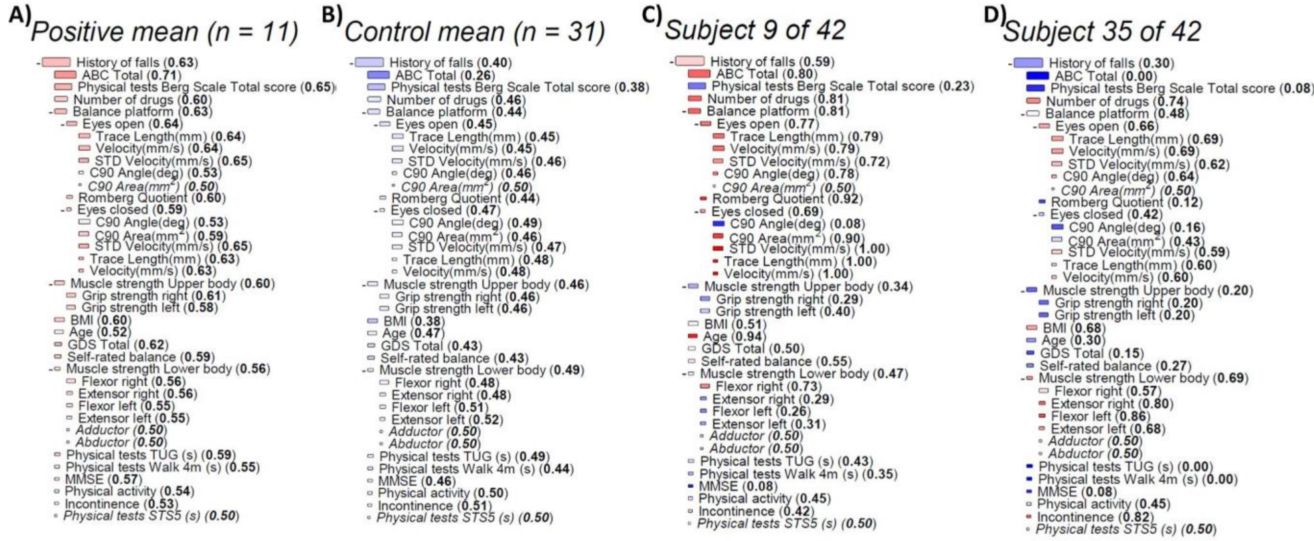

Figure 1. DSF visualizations for A) mean of fallers group, B) mean of non-fallers group, C) example case from fallers group, and D) example case from non-fallers group. The tree visualizations are opened to show all the 32 used features. All the available items from balance platform and the individual questions from ABC, BBS and GDS scales are not included besides the total scores. The size of the node boxes show the relative relevance of each feature and the numbers indicate the similarity to the positive (fallers) class.

The DSF is used as a supervised classifier with leave-one-out cross validation method to investigate the ability of DSI value in separating fallers from non-fallers. A DSI value over 0.5 suggests the subject belongs to the fallers group and below 0.5 refers to the non-fallers group respectively. Furthermore, different grouping criteria is tested by applying the total score from ABC test, and more specifically the level of physical functioning, to form the two reference classes.

When also the individual questions or tasks are included from ABC, BBS and GDS scales, the total number of features considered in this analysis is 103.

III. Results

The DSF visualization for fallers (positive) and non-fallers (control) group means are presented in Fig. 1 with example cases from both groups. The *ABC total score* followed by *BBS total score* and *number of drugs in use* were the three most relevant features, that differed the most between the two classes. The visualizations of the example cases C) and D) show that both have individual assessment results that refer to the opposite class. For example the subject in Fig. 1 C) had *BBS total score* similar to the non-fallers' group, while *ABC total score*, *number of drugs in use* and *overall balance platform leaf value* features were comparable with the fallers' group results.

Classification of subjects into fallers and non-fallers based on their resulting DSI value and the leave-one-out cross validation method yielded sensitivity of 54.5% and specificity of 64.5%. When the subjects were divided into two groups based on the ABC result, the classification results with the same features as in Fig. 1, except replacing *ABC total* from the leaves with *history of falls*, gives sensitivity of 71.4% and specificity of 88.6%.

When testing the individual items from different scales all the 103 features were inserted to the DSF directly under the root to investigate which of them differ the most between the groups of fallers and non-fallers. The ten most relevant features were mostly from ABC questionnaire: 1) *ABC question 5*, 2) *ABC total score*, 3) *ABC question 13*, 4) *ABC question 10*, 5) *BBS task 11*, 6) *ABC question 4*, 7) *ABC question 9*, 8) *BBS total score*, 9) *ABC question 15*, and 10) *Balance platform Eyes closed Standard deviation in X direction*. Classification with this tree structure resulted in sensitivity of 54.5% and specificity of 80.6%.

IV. Discussion

This paper presented a novel application of DSF in fall risk analysis. A clear benefit and potential of the DSF visualization is that it allows inspection of multiple assessment scales and factors at a glance. In addition, it enables detection of significant factors for the individual, as it became evident also in this study sample that the assessment scales indicating fall risk for one person might not reveal the risk for the other. This confirms the fact that people have problems in different areas and one single assessment scale is not enough to expose all the people at risk. The visualization method represented here allows rapid interpretation of large amount of data and can be utilized in selecting the most relevant assessment scales.

The results with this study sample indicated that the *BBS total score* was the second most relevant feature in separating fallers from non-fallers. Similar results were achieved in [9] and [10], where regression analysis was used to form a model for either predicting falling or separating fallers from non-fallers. Furthermore the *ABC total score*, that was the most relevant in our study, was also found significant in [10]. However, when investigating individual items of the ABC scale, the most relevant questions were not the same. In this study, question 5 (confidence when standing on tiptoes and reaching for something above head) was the most relevant item from the ABC scale, and also from the whole set of included features. Whereas, the question 1 (walking around the house) was the most significant in study [10]. The test subjects in this study were in relatively good physical condition, due to which they might generally feel confident when walking around the house and the difficulties come up with more difficult tasks, such as described in question 5. This is important finding, since developing technologies for early risk detection is more crucial in the current ageing population; we need to find out more accurate discriminating factors earlier to start early prevention.

The DSF can be utilized with different grouping criteria of subjects, as was demonstrated with the ABC scale result. This grouping yielded the highest sensitivity and specificity of classification, but more data is needed to validate the results. The small sample size and relatively good condition of all of them affects especially the classification results, since two clearly divergent groups cannot be distinguished based on the data. Another interesting grouping criteria could be e.g. the total BBS score. Although the current sample has relatively high BBS scores with the average of 53 out of 56 points, it appeared to differ between the fallers and non-fallers.

This research had some limitations, which need to be taken into account when exploiting the results. The limited number of subjects were in relatively good physical condition and the group of fallers was clearly smaller compared to non-fallers. In order to verify the method's ability to estimate true fall risk, follow-up data from actual fall incidents after the baseline assessment should be collected. In addition, the classification performance of the algorithm should be compared to other commonly used approaches. The objective of our future work is to utilize also the accelerometer and depth camera data by studying how different sensor features correlate to the total fall risk, different clinical assessment scales and individual fall risk factors with the DSF algorithm. The same subjects will be invited to follow-up assessment to study possible changes in their condition and thus in different measures.

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