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Application of Artificial Neural Networks in Fall Prediction

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Abstract The problem of fall is still unsolved even though it is a serious problem, especially in group of elderly. Also, another difficulty is to analyse falls that occur in day-to-day life. Those events are hard to observe by specialists and so it is hard to analyse them. Following work contains a description of experimental process for external force-caused fall observation with the use of motion capture system and dynamometric platforms. Data collected according to this protocol were later used for time series neural networks. Obtained results of analysis were compared to popular model of human stability. Conducted inquiry proves that it is possible to detect fall even before it occurs and while it is external force-caused fall the loss of stability develops earlier than it was assumed.

Keywords: fall detection, time series neural networks, motion capture, stability

1. Introduction

One of the most essential factors that has influence on human stability is the base of support (BOS) - its size and quality. While maintaining standing position with both lower limbs touching ground it is determined by the area around feet, as it is shown at Fig. 1. As the position is changing while performing subsequent movements, the size and shape of the BOS changes. While standing on one leg the size of BOS is equal to the area of contact between one foot and ground, while using a cane the area enlarges to enring the area of contact between cane and feet with the base, etc. The aforementioned "quality" of the BOS is determined by sizes of three areas that can be distinguished inside of this zone – AS (area of sways), IBS (individual boundary of stability) and BS (boundary of stability). Depending on age, physical condition etc. the range of AS changes. The less efficient the equilibrium is, the smaller IBS and the larger safety margin (SM) gets. The COM (center of mass) area shown on Fig. 1 represents the movement border of the center of mass projection on the base of support. While performing movements in standing position the location of COM area changes. If it will leave the IBS region there might occur loss of stability hence, the fall or there will be need of use of support. According to this assumption, as long as the COM remains before the line determined by ankles, it is possible to return to a stable position. However, if this board will be crossed (the COM leaves IBS area) there is a strong probability that fall will occur. Moreover, it is assumed that this borderline appears about 5-7 cm from center of the area of COM occurrence during stable standing. Therefore, it can be assumed that human is still capable of returning to a stable position when projection of center of mass moves 5-7 cm backwards [1-3].

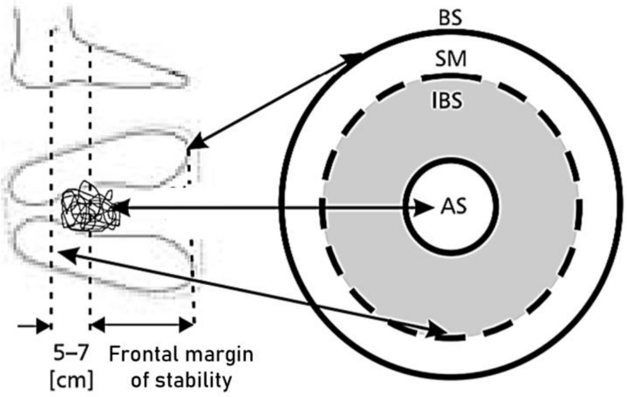

Fig. 1. Heuristic model of human stability [3].

To determine the size and shape of the base of support and its areas the examination called posturography is often performed. The main goal of posturography is to assess the ability of standing upright under various conditions. Those conditions may be both statical (examined person stands still on a stable surface without any external disruptions) and dynamical. During the examination of second type moving platforms, external stimuli on the upper or lower body part or different movements generated by patients themselves (lifting weights, voluntary movements etc.) are performed to unsettle the assessed person's position. The external stimulus can be performed by pulling or pushing the participant of study. The force is often applied to the area of the patient's pelvis or shoulders. During examination the posturography plate is being used, so it is only possible to capture movements of the center-of-foot-pressure (COP) in time. During more precise examinations motion capture systems, accelerometers or electromyography equipment are used [4-6].

While keeping a stable standing position two main groups of strategies can be distinguished: corrective and protective. The characteristic feature of the first group is a constant base of support. The position of the center of mass is being corrected only by sequences of muscle activation, which begins from contraction of muscles around the ankle (the ankle strategy) or by contraction of muscles around the hip joint and torso and then lower limb muscles are activated (hip joint strategy). During performance of strategies of the second type - protective ones - there is a change of the BOS. To maintain a stable position there is a need to perform a step (step strategy) or to get a support on a cane, wall, chair etc. to prevent falling down (support strategy) [1,7].

2. Methods

2.1. Data acquisition

The main assumption of the performed study was to obtain data about external force-caused falls (force applied around pelvis) and data of movements in the sagittal plane but did not end with fall (backward-forward swinging, sitting, performing sit ups). There was made an assumption, that only events where there were no changes in BOS's size or shape will be analyzed. Therefore, participants of the study were asked not to move their feet - perform only corrective strategies. Types of captured events are presented in Tab. 1.

Tab. 1. Types of captured events.

fall event	non-fall event
as an effect of applying external force rapidly	as an effect of applying external force rapidly
as an effect of applying slowly increasing force	as an effect of applying slowly increasing force
	other events: squat, forward-backward swinging, sitting

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The optoelectronic motion capture system - BTS Smart-DX 6000 - and dynamometric AMTI plates were used for data acquisition. The sampling rate of all cameras registration was 100 Hz, whereas signals from platforms were collected with 500 Hz frequency. Therefore, in further steps of analysis after data were obtained frequency of data about reaction forces had to be reduced.
To capture positions of essential body parts - torso, pelvis and lower limbs - passive markers were placed as shown on Fig. 2. Unfortunately, there was no possibility of placing markers on the back of study participants due to the specific character of the study.

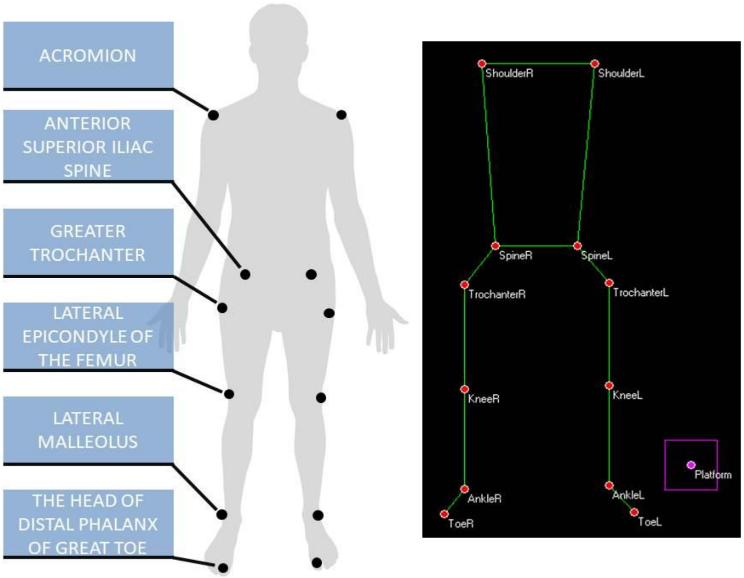

Fig. 2. Passive markers placement.

To simulate external force-caused falls the participants of the study had half body climbing harness on and force was applied by pulling the rope attached to the harness as shown on Fig. 3. The force was either slowly increasing or had a character of rapid pull. Due to climbing harness use the force was applied around the approximate center of mass, which allows us to assume that captured events are close to real external force-caused fall, which may occur in daily life, for example during rapid bus braking. During data acquisition there were mattresses behind the participants to prevent injuries.

Fig. 3. Experimental setup.

The study was performed on a group of n<10 participants in mean age 23±1.15, weight 57.5±7.11 kg and height 1.65±0.07 m. Each of participants gave data of at least 50 records and on each record consisted of at least one event. Therefore, the sum of 226 fall events and 371 non-fall events data were obtained.

2.2. Data preparation for neural network

With the use of captured markers positions the position of the approximate center of mass was calculated. Acquired COM position was then projected on the plane of base of support (aCOM point) and its' distance to line of ankles (markers named *ankle*) was calculated. The change of this distance in time for one of the captures (4 rapid pulls, the least ended up with the fall) is shown on Fig. 4. According to the aforementioned assumption one event gives one data set therefore, out of the presented record 4 sets were obtained - 3 non-fall and 1 fall event.

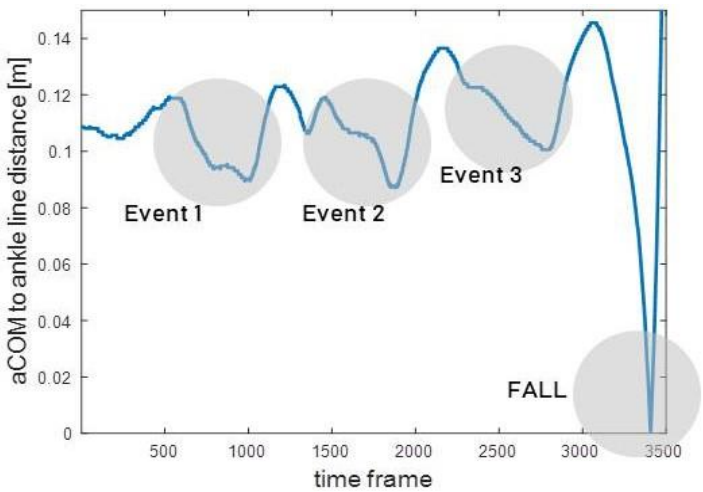

Fig. 4. Change of distance *d* of projection of approximate center of mass aCOM from the line of ankles.

Acquired data were inputs for neural networks. On the output of the network the value {0,1} was expected if the fall event was not detected and {1,0} if the fall occurs. In the learning dataset change of state form {0,1} to {1,0} was defined by the distance of aCOM from the line of ankles (Fig. 5). Therefore, 14 datasets were prepared - for various time frames of state change. All of the input data were normalized to include in range <0,1>.

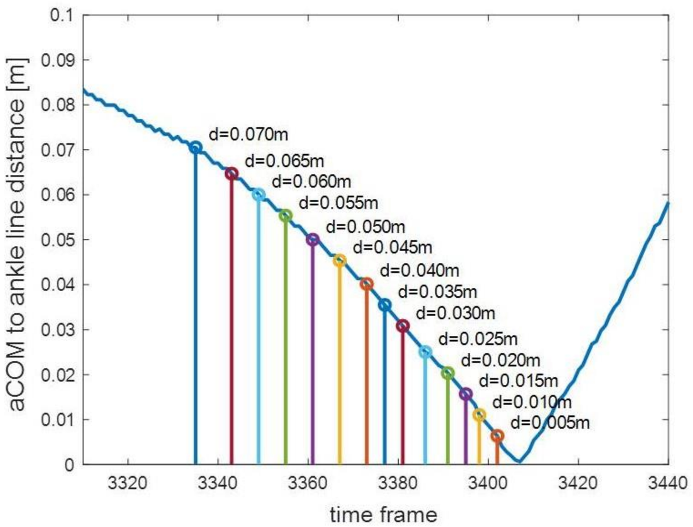

Fig. 5. Time frames of state changes in subsequent analyses.

Time series neural networks were used for this analysis and all of the work was performed in MATLAB. The inquiry was conducted in two scenarios - with learning process performed in parallel architecture (PA) and series-parallel architecture (SPA). Testing of acquired neural net was performed only on parallel architecture (PA). The main difference in those two architectures is that the parallel architecture the backpropagation occurs and to calculate input value for next time frame there is taken output value from previous time frames. This output is calculated by network itself. The series-parallel architecture also takes for the input data output from previous time frame, but there is no backpropagation [8]. This value is taken from another dataset of expected output values. So, there were two analyses conducted - SPA-PA and PA-PA. To assess efficiency of learning and testing of the networks three parameters were calculated: P_m, P_{m+1} and P_{end}. Each of them was obtained with the use of same equation, but they were calculated for different time frames of sequence. The P_m parameter gives information about the accuracy of prediction in the time frame, in which to fall occurs - the change of output state from {0,1} to {1,0} was predefined. The P_{m+1} parameter refers to the accuracy in next time frame and P_{end} gives information about the accuracy in the last time frame in sequence. One can notice that the third parameter gives information if the network classifies the event as fall or non-fall correctly, regardless of time frame in which the fall will be recognized. Values of those three parameters were calculated as follows:

$$P = \frac{|\widehat{y_i} - y_i|}{s} \cdot 100\%, \tag{1}$$

where P is the value of parameter, $\widehat{y_i}$ is the expected value on the output of neuron in time frame i, y_i is the obtained output value in the time frame i and s is the number of samples in the data set given for the neural network. Using acquired data on the input of network were given information about: ground reaction forces (three components), position of right shoulder (three components), its velocity and acceleration. Those two factors were calculated using first and second degree derivate from position of marker placed on pelvis.

3. Results

In the table below (Tab. 2) the values of parameters P on learning and testing networks in architectures SPA-PA and PA-PA for chosen d distances are shown. It is worth to pay attention on significant differences between values of P_m and P_{m+1} on learning stage of architecture SPA-PA. It occurs as the result of specific architecture of SPA neural net – the change of output state from {0,1} to {1,0} is forced by the architecture of the net. Time series neural network in learned in series-parallel architecture should be more effective in detection the exact time frame of fall. This tendency is also visible on Fig. 6. P_{m+1} and P_{end} values for SPA-PA are close to 0, whereas the error calculated for time-frame of state change P_m is the largest of all. Aforementioned assumption, that SPA-PA architecture is more suitable for exact time frame of fall recognition can be proved while comparing values of P parameters for subsequent distances d (Fig. 7). Time series net, which was learning with closed-loop architecture PA obtains similar values of P, regardless of the time frame in which its state was changed from non-fall to fall. Whereas, it is clearly visible that net SPA-PA is more likely to change its ability to non-fall/fall classification. When aCOM is closer to the line of ankles than 25 mm SPA-PA net classifies events with better results.

Tab. 2. Values of P parameters for learning and testing processes for chosen distances d for both of neural net scenarios – learning on architecture SPA-PA and PA-PA.

distance d [m]	learning (L) \testing (T)	P_m [%]		P_{m+1} [%]		P_{end} [%]	
		SPA-PA	PA-PA	SPA-PA	PA-PA	SPA-PA	PA-PA
0.005	L	29,68	16.40	1.53	8.80	0.82	4.57
	T	29.06	21.62	29.12	21.76	29.11	18.55
0.025	L	28.96	17.41	0.57	12.63	0.57	3.49
	T	19.98	22.19	20.62	22.23	17.49	14.22
0.050	L	28.85	19.26	0.67	15.97	0.61	5.38
	T	72.93	20.92	73.80	20.32	69.62	13.24
0.070	L	20.76	17.14	0.55	14.16	0.50	5.55
	T	40.47	17.33	39.82	16.77	33.02	11.57

While comparing global results of neural networks outcomes in testing state it can be noticed, that PA-PA obtains lower values of errors, despite having worse results in learning stage than SPA-PA. Therefore, it can be concluded that neural net learnt by closed-loop architecture is more suitable for detection whether the fall tool place at all, without recognition of the exact moment of fall.

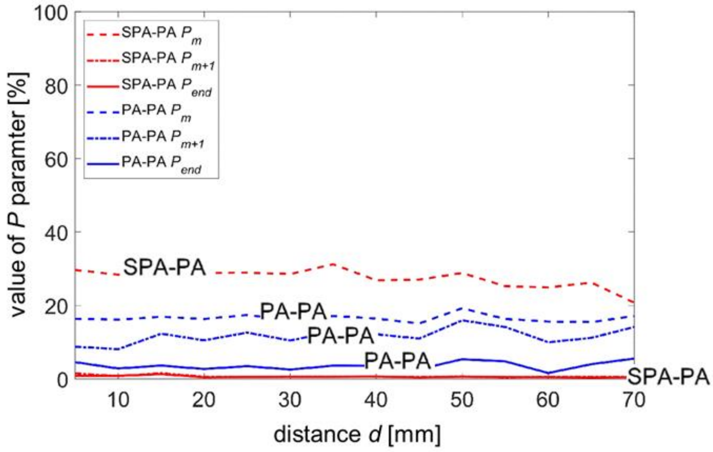

Fig. 6. Comparison of *P* values during learning process for successive *d* values for networks in architecture SPA-PA and PA-PA. Input data: all events.

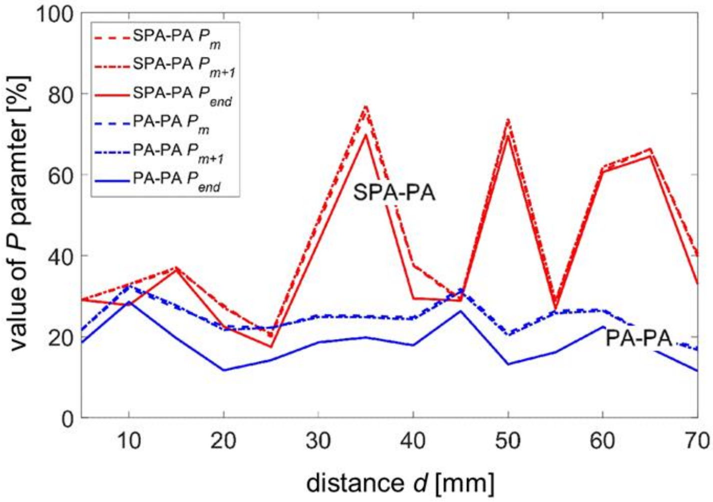

Fig. 7. Comparison of *P* values during testing process for successive *d* values for networks in architecture SPA-PA and PA-PA. Input data: all events.

In the next step of analysis data about events described earlier as *other* (bottom row of Tab. 1) were excluded from input dataset. Therefore, the amount of input data had been reduced but the ratio of dataset (4:1) was preserved. In learning dataset 240 sequences were used and in training one – 60 sequences. The comparison of effectiveness of fall detection by both networks depending on *d* distance determining the time frame of fall is shown on Fig. 8. The comparison pertain to the P_m error values. One can notice, that after excluding *other* events from dataset error values are greater than during analysis of all captured events.

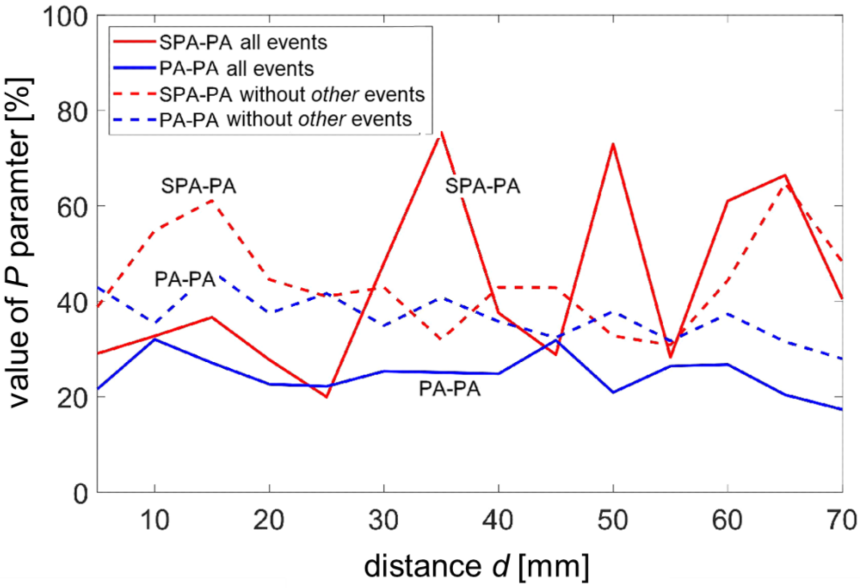

Fig. 8. Comparison of P_m values during testing SPA-PA and PA-PA networks with and without *other* events in input dataset.

4. Conclusions

Presented data acquisition technique allows to simulate external force-caused falls under laboratory conditions. The motion capture systems are commonly used in motion biomechanical studies, e.g. gait [9,10,11] or jump [12] analysis or FMS test validation [13]. Due to motion capture use it was possible to thoroughly analyse the issue of fall with later use of artificial neural networks. It should also be noted that only falls in the sagittal plane were investigated. Such a fall under the action of a random force can simulate a fall that occurs in everyday life, e.g. in public transportation.

Conducted analysis proved, that it is achievable to detect the fall even before it happens. Moreover, on the basis of obtained results it can be assumed that the loss of stability leading to a fall occur when COM projection on the base of support is approximately 25 mm before the line of ankles, thus it is earlier than it is assumed in aforementioned heuristic model of stability. Further analysis of the issue provided a remark that excluding *other events* from input dataset causes a reduction in effectiveness of neural network outputs. While planning further research, it should be taken into account to capture movement that could be misclassified as falls. However, the problem of human fall is complex and for a multiplane analysis using the tools proposed in the paper, the research group and the number of events should be significantly increased.

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Additional information

The authors declare no competing financial interests.

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