Kinect-based gait analysis for automatic frailty syndrome assessment

KINECT-BASED GAIT ANALYSIS FOR AUTOMATIC FRAILTY SYNDROME ASSESSMENT

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ABSTRACT

Smart living and well aging represent key challenges for our society. The precursor state of adverse outcomes that characterize aging has been recognized from scientific community with the frailty syndrome, determined by the loss of physical and psychological capacities. In this paper we define gait and posture indexes that can be effectively and unobtrusively measured using computer vision and RGBD sensors, e.g. the popular MS Kinect. In this study we present preliminary results showing evidence that the proposed approach can pave the way to the design of an automatic and objective tool for detection and early prevention of frailty.

Index Terms— Gait analysis, Computer vision, Kinect, Frailty

1. INTRODUCTION

Populations around the world are rapidly aging. Life expectation has been increasing from 64 to 71 years between 1990 and 2015 in most developed countries worldwide. The number of people 60 and older reached 901 million in 2015 and will increase by 56% to around 1.4 billion people in 2030, of whom over 650 million will be 70 or older [1]. This dramatic increase of elderly individuals represents serious challenges in terms of demand for healthcare. In fact, aging is associated with the prevalence of chronic diseases, dependency in carrying out the activities of daily living, disability, institutionalization, falls, fractures, cognitive decline and onset of dementia [1].

The precursor state of adverse outcomes that characterize aging has been recognized from scientific community with the syndrome of frailty. There are many definitions of frailty: it is defined as the "loss of physiologic reserve" and an increased vulnerability to external stresses [2, 3, 4]. The elder frail individuals account for the highest health care costs in industrialized countries [5]. Early identification and treatment of people with a pre-frail syndrome, an earlier stage of the physiological decline, may help delay or postpone the onset of frailty and its negative consequences with substantial positive impact on the entire society. One of the major indicator of frailty concerns to the impaired physical functionality, mainly assessed by analyzing the locomotion, or gait [4].

Nowadays, frailty is mainly assessed with self-report questionnaires. In the physical domain, the most used and known test is the Timed Up and Go test (TUG) [6], a simple test to assess the person's mobility. The test is used to compute the time that a person takes to get up from a chair, walk three meters directed to a cone, turn around, walk back to the chair and sit down. The total time spent in the completion of these steps is the final outcome of TUG. A large TUG time is related to a lower physical function and it is often used as an indicator of physical frailty. Other assessment methods are based on questionnaires such as the Tillburg Frailty Indicator (TFI) [7, 8]. TFI is a simple and easy tool to assess frailty and gives a total score of frailty ranging from 0 to 15, with a cut-off score of 5. These frailty tests are afflicted by several drawbacks. The questionnaires require a lot of time to be filled, some questions may be difficult to understand by older individuals and the self-reported measures may be prone to bias. Moreover, the only parameter measured by the TUG test is the total time for performing the gait sequence, but it may be not enough for detecting the physical frailty. New methodologies for assessing frailty are currently being studied and computer vision can overcome the limitations of the classical approaches just described. On one hand, it allows to implement an automated approach for the extraction of frailty indexes and, on the other hand, it is able to see beyond what the human eye can, and in an objective way.

In this paper we present a prototype of a frailty detection tool, based on the analysis of video sequences acquired through the popular RGBD sensor Microsoft Kinect during the TUG test. Our first contribution is the definition of a set of gait and posture features that can be computed automatically using the Kinect. Then we show that such features are indeed correlated with the impaired physical functionality. Finally, we compare the results obtained with the proposed automatic tool with the outcomes of the manual TUG test and validated self-report questionnaires on a sample of 30 subjects. This analysis allows us to unveil the possible correlation between the proposed indexes, that can be measured objectively and automatically, and the onset of frailty in aging population.

The paper is organized as follows: in Section 2 an overview of the state of the art about the gait analysis for health purposes is given. In Section 3 our method for extracting gait parameters is outlined, while in Section 4 the experimental analysis is described. Conclusions are drawn in Section 5.

2. RELATED WORK

Gait analysis is the study of human locomotion; kinematic and kinetic data are acquired and analyzed for different purposes. The clinical application of gait analysis allows the clinician to evaluate physical impairments that could be related to different diseases and disorders [9]. There are several examples of healthcare applications for assessing the postural balance [10], rehabilitation [11], monitoring of elderly people for falls detection [12] , evaluating the health index and the frailty syndrome in older adult [5, 13, 14, 15], and so on.

In recent years the Kinect has been used for the analysis of human movement in many areas including health applications. In [16, 17] it is shown that gait features extracted from Kinect can be

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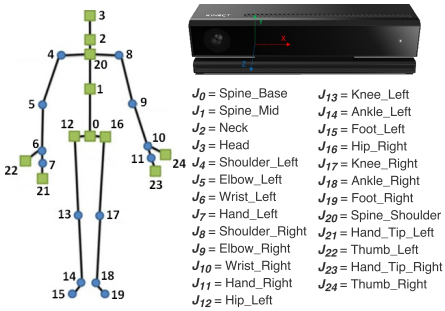

Fig. 1. Skeleton map and coordinate reference system of the Kinect sensor v2.

used as a biometric signature. Gabel *et al.* [18] have performed full body gait analysis for continuous gait monitoring at home. Obdrzalek *et al.* [19] have investigated the accuracy of Kinect pose estimation for evaluating physical exercises aimed at coaching of elderly population. Paolini *et al.* [20] have combined Kinect tracking and virtual reality environments for gait training program on treadmill for improving gait and mobility in patients with neurological impairments. Yang *et al.* [21] have investigated the reliability of the sensor for evaluating standing balance for postural control. There are many examples of Kinect usage for in-home monitoring of elderly, especially for fall risk assessment: measuring of stride-to-stride gait variability [22]; monitoring of human centroid height relative to the ground and body velocity [23]; testing a two-stage fall detection system [24]; implementing the five-times-sit-to-stand (5STS) test, a functional test to assess fall risk and discriminate between fallers and non-fallers [25].

We can mention few examples of the use of Kinect combined to the TUG test, but not properly related to the frailty assessment which, to the best of our knowledge, has not yet been investigated in the literature. Stone *et al.* [26] have developed an in-home Kinect based monitoring system for estimating the TUG time and the walking speed, with the purpose to map the in-home gait data to a domain that clinicians understand. Hassani *et al.* [27] have presented a 3D computer vision system for rehabilitation of the frail elderly in home environment. They have analyzed the TUG movements, in particular the transfer from sitting-to-standing and back-to-sitting. Vernon *et al.* [28] have examined the reliability of the Kinect measures during common clinical tests such as the TUG one, for individuals living with stroke.

3. PROPOSED METHOD

In this study we propose to carry out gait analysis by using the Kinect sensor, the widespread and cheap Microsoft's RGBD camera, to extract features that are potentially correlated with the onset of the frailty syndrome. The Kinect sensor exhibits several advantages: it allows real-time tracking of the body movements, without markers or any camera calibration and environment setup. In particular, we used the skeleton tracking feature of Kinect for Windows version 2. The new skeleton map is made up of 25 joints, five more than the previous version, and the joints tracking is more accurate and stable [29]. In Figure 1 a picture of the sensor together with the coordinate reference system, the skeleton map and the joints labels is shown. In the following let us define $J_k^i = \left(J_{k,x}^i, J_{k,y}^i, J_{k,z}^i\right)$ as the i-th acquisition of the coordinate of the k-th joint.

We base the assessment of physical frailty on gait analysis and the concept of gait cycle, or stride, i.e. the sequence of movements between two stationary positions of the same foot while walking. During this cycle it is possible to detect two kind of parameters: spatial-temporal measures, such as *speed*, *swing time* (i.e. the part of the stride time in which the foot swings in air), *double support time* (i.e. the time in which both feet are in contact with the ground), variability of stride velocity, mean duration and variability of a single walking sequence, and so on; postural balance features, related to the skeleton posture during motion. For evaluating the frailty it is important to consider both of these parameters [5, 13, 25].

The experimental setup is arranged in accordance to the well known TUG test, where the subject is asked to get up from a chair, walk along a 3 m line (forward and backward) and sits again. To capture the movement with the sensor view frustum we placed the Kinect at a distance of about 4 meters from the chair at a height of 2 m. During the TUG it is quite trivial to substitute the usual manual timing of the test using the skeleton tracking data. For computing TUG time, denoted in the following by T, one can implement an automatic procedure able to trigger a timer when a subject gets up from the chair and to stop it when he/she sits again. As an example this can be achieved by monitoring the mutual position of the skeleton joints. Unfortunately, in the default configuration of the test, the chair turns out to be at limits of the depth range of Kinect, where the skeleton data are very noisy and unreliable. Given this limitation, in this study we kept using the manual TUG timing, whereas the sensor is used to extract features during the walking phases only.

The spatio-temporal and postural balance features are extracted by analyzing the gait cycle in terms of skeleton joints position measured by Kinect using the RGBD video. The fist step of our method is to select only the video frames where the subject is completely inside the camera view frustum, in order to reduce acquisition errors and to collect reliable measures. To this end, we select only the frames where the entire skeleton is tracked.

The gait sequence acquired during the test can be divided into two parts: the first one in which the subject walks towards and facing the camera; the second one in which the subject walks back to the chair. In this second part of the gait sequence we need to invert the value of the left and right joints (i.e. those of arms and legs) because Kinect does no provide any automatic mechanism for this kind of situation. For detecting the turning point we check the depth value of the center of mass ($J_{0,z}^i$): it should be strictly decreasing when the subject walks towards the camera and strictly increasing when he/she comes back to the chair. To this end, we assume a forward acquisition when $J_{0,z}^i - J_{0,z}^{i-\Delta} < 0$ and a backward one, otherwise. Our experiments show that the detector is stable and reliable when setting $\Delta = 2$.

The core of the proposed gait analysis tool is represented by Algorithm 1, that we designed to update the gait features as soon as a new stride is detected. The pseudo code refers to the case of the left stride. In our implementation we repeat the same steps on both right and left strides. Stride detection is based on the ankles joints whose estimated positions turn to be stabler than the feet joints (see our previous analysis in [16, 17]).

In particular, the beginning of a new stride is detected at time t_S as soon as $d(J_{14}^{t_S}, J_{14}^{t_S-\Delta}) > d_{tol}$, where d_{tol} is a proper threshold value and $d(\cdot,\cdot)$ represents the Euclidean distance between a pair of joint coordinates. In other words, when we observe a significant variation in the position of the ankle we assume that the corresponding foot is moving (the flag $isLeftFootMoving$ is set to TRUE). Based on our experimental analysis we set $d_{tol} = 5$ cm. Similarly, the stride is assumed to end at time t_E if $isLeftFootMoving$ is

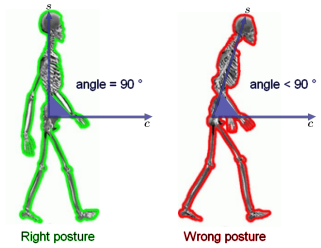

Fig. 2. Postural balance during walking: right and wrong postures.

equal to TRUE and no further movement is detected applying the same criterion. The difference $(t_E - t_S)$ is an estimate of the swing time defined above. In this work we use as a gait feature the total swing time ζ defined as the summation of the times of all the detected strides. The detected stride also serves to estimate the distance covered by the subject while walking. Therefore, we compute the covered distance δ, where all strides are progressively completed. To this end the Euclidian distance between the coordinates of the center of mass J_0, at time t_S and t_E respectively, is used to approximate the actual movement. Moreover, through the same stride detection strategy we also compute the total walking time τ, defined as the difference between the t_E of the last stride and t_S of the first stride, respectively. In other words, τ represents the time elapsed from the beginning to the end of the walking exercise. The double support period, i.e. the time spent with both feet on the ground, can now be approximated as the difference between the walking and swing time $\eta = \tau - \zeta$. Furthermore, δ and τ are used to estimate the walking speed $\beta = \delta/\tau$.

Algorithm 1 Extraction of spatio-temporal gait features

```
δ ← 0
ζ ← 0
for each frame i in which whole skeleton is TRACKED do
    # detection of the LEFT foot
    if d(J_14^i, J_14^{i−Δ}) > d_tol then
        if !isLeftFootMoving then
            isLeftFootMoving ← TRUE;
            t_S ← i;
        end if
    else
        if isLeftFootMoving then
            isLeftFootMoving ← FALSE;
            t_E ← i;
            δ ← δ + d(J_0^{t_S}, J_0^{t_E});
            ζ ← ζ + (t_E − t_S);
        end if
    end if
end for
return [δ, ζ]
```

During the TUG test, we estimate also the postural balance of the subject. To this end we extract a measure related to the torso inclination during the walk; this feature can predict if the subject is excessively tilted forward, increasing the fall risk. Looking at the Figure 2 one can note a right posture (on the left) and the wrong one (on the right). Let us consider two axes: c is the axis passing through the center of mass (J_0) oriented along the walking direction, and parallel to the floor plane; s is the axis passing through the spine joints (J_0, J_1, J_2). If the posture is correct, c and s form an angle ϕ approximately equal to 90°; otherwise, if the torso tilts forward, ϕ becomes smaller.

For better clarity, all the defined gait and posture features are collected in Table 1.

Table 1. Collected features during TUG test.

Label	Features
T	TUG test total time
τ	walking time
δ	covered distance
β	walking speed
ζ	swing time
η	double support time
ϕ	torso inclination angle

4. EXPERIMENTAL RESULTS

The validation of the proposed features for frailty detection requires an interdisciplinary approach. To this end the experimental phase has been worked out with the collaboration of experts in the field of active and healthy aging from the Psychology Department in our university. In particular, we were able to test the proposed automatic gait analysis tool in a real scenario by setting up an experimental trial for the assessment of frailty syndrome involving 30 senior subjects in the Turin area. Most of the participants were female (83.3%) and the mean age was 75.6 $\pm$ 7.5 years. The participants were asked to fill the TFI questionnaire; in particular, in this study the total score of the TFI in addition to the 8 items of the TFI physical domain have been considered [8]. The TFI is a recognized instrument for frailty detection and can be used to unveil correlation between other objective features and the onset of the syndrome. The TFI was filled directly at elder's home, while the TUG tests with the MS Kinect sensor were performed at senior centers in town. Therefore, the only difference with respect to the classic test is the presence of the sensor for capturing the gait parameters.

4.1. Gait features analysis

The first objective of our experimental analysis is to figure out if the movement parameters detected by Kinect allow to identify physical dysfunctions. To this end, we make a comparison between the gait samples of the elderly people and 6 additional young healthy subjects, who underwent the same test. We start presenting an analysis of the spatio-temporal gait parameters, to continue with an evaluation of the postural balance features.

The average time spent by the 30 subjects in performing the TUG test is $T = 11.42 \pm 3.22$ s, while the 6 subjects takes on average 9.66 $\pm$ 2.09 s to complete the test. The walking time turns out to be $\tau = 9.31 \pm 3.11$ s for elderly people and 7.16 $\pm$ 1.66 s for young people. Comparing these first results it is easy to see that, as expected, the young people take less time with respect to the elderly ones to perform the test. It can be noted that for the young ones T is slightly greater than the walking time τ. This is a reasonable result since younger people take a shorter time to get up from the chair and sit down. Both elderly and young subjects covered similar distances $\delta = 6.70 \pm 0.57$ m and 6.57 $\pm$ 1.20 m respectively; such results are very close to double of the actual distance between the chair and the turning point and allowed us to validate the accuracy of the proposed stride detection algorithm.

In Figure 3-(a) we show the walking speed β measured on the 30 tested subjects. In all the following graphs the average value yielded by the young ones is shown for comparison (solid line). The walking

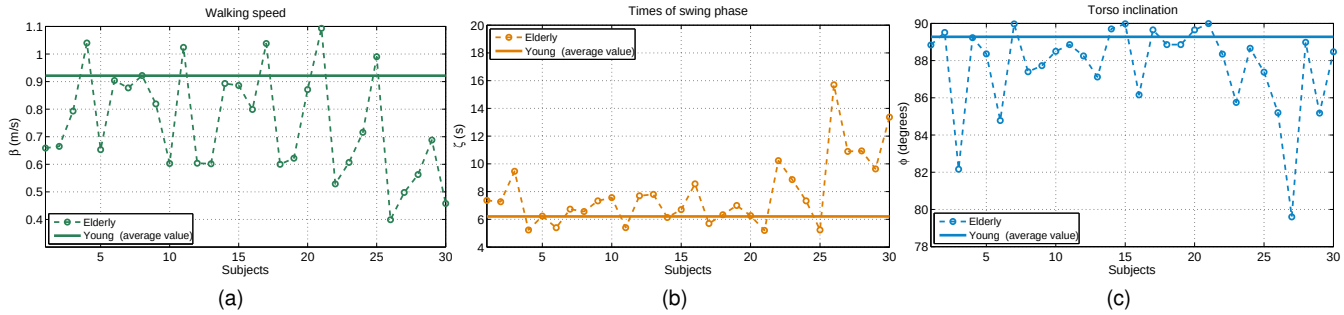

Fig. 3. Spatial-temporal and postural balance gait parameters.

speed is $\beta = 0.75 \pm 0.19$ m/s for seniors and 0.92 ± 0.07 m/s for youth. These results confirm that the proposed method is producing meaningful measurements. In [5] similar speed values have been already estimated: the authors reported on average 1 m/s for a non-frail person, 0.7 m/s for a pre-frail person and 0.5 m/s for a frail person. Our experiments confirm these previous findings: the young people have a normal value speed of about 1 m/s, while the elderly subjects are on average in the pre-frail range.

In Figure 3-(b) the swing time ζ is shown. The average value is equal to 7.81 ± 2.48 s for elderly people; this is larger than the average value of 6.21 ± 1.67 s exhibited by young people. The same trend can be noted for the double support measurement, which amounts to $\eta = 1.50 \pm 0.86$ s for seniors and 0.94 ± 0.38 s for the young. Age-related changes worsen the balance during walking, and for this reason older people need more time in all the walking phases (such as swing phase and double support phase) in order to be able to transfer themselves without falling down.

Finally, the torso inclination (shown in Figure 3-(c)) is $\phi = 87.70 \pm 2.40°$ in the case of elderly subjects while it is equal to $89.28 \pm 0.80°$ in the case of young subjects, highlighting the different posture. Moreover, our results show that subjects 3, 6 and 27 have an inclination of about 85°, that might increase the falling risk.

4.2. Gait features and frailty assessment

Now we focus on comparing the indexes yielded by 3 different approaches, namely TFI self reports, TUG time, which are standard manual methods, and the automatic tool proposed in this work. TFI will be used in the following as a reference for frailty assessment. The average TFI score of the tested population is equal to 4.79 ± 2.54 points. Specifically, 13 subjects (43.3%) were detected as robust (score lower than 5), while 17 (56.7%) were considered frail.

In Table 2, we compare the TFI scores and the objective metrics acquired on the 30 subjects by computing the Pearson's correlation coefficient r. We also computed the significance of the achieved empirical correlation in terms of p-value (the lower the p-value the higher the confidence on the estimated correlation).

Our results confirm that the TUG time T is significantly correlated with the TFI, both total score TFIts and physical domain TFIpd [8]: $r = 0.470$ (p-value $= 0.012$), $r = 0.473$ (p-value $= 0.011$), respectively. More importantly we can notice that most of the proposed gait features correlates with the TFI as well. In particular, the walking time τ yields $r = 0.422$ (p-value $= 0.025$) and $r = 0.421$ (p-value $= 0.026$) with TFIts and TFIpd respectively; for the walking speed β we report $r = -0.483$ (p-value $= 0.009$) and $r = -0.496$ (p-value $= 0.007$). It is worth pointing out that the features that are related to the swing and double support phase of the gait are signficantly correlated with TFI as well. In particular we get $r = 0.390$ (p-value $= 0.040$) and $r = 0.396$ (p-value $= 0.046$) for ζ and $r = 0.380$ (p-value $= 0.037$) and $r = 0.366$ (p-value $= 0.05$) for η. The only feature that does not correlate well with TFI is ϕ, that is related to posture. Nonetheless, it can be noted that ϕ is correlated with T suggesting that posture may be an aspect neglected by TFI.

Table 2. Pearson's correlation coefficients r between proposed metrics and TFI score ($*$: p-value < 0.05; $**$: p-value < 0.001)

	T	TFIts	TFIpd
T	–	0.470*	0.473*
TFIts	0.470*	–	0.912**
TFIpd	0.473*	0.912**	–
τ	0.978**	0.422*	0.421*
β	-0.834**	-0.483*	-0.496*
ζ	0.952**	0.390*	0.396*
η	0.785**	0.380*	0.366*
ϕ	-0.403*	0.143	0.088

In conclusion, the analysis of the correlation between the score of manual questionnaire results and the proposed features show that our objective and automatic indexes are quite promising indicators for the frailty syndrome.

5. CONCLUSION

In this paper we have proposed novel gait and posture indexes that can be measured using MS Kinect sensor with the goal to assess the onset of the frailty syndrome in older adults. In this study we have shown promising results giving evidence that the proposed approach can pave the way to the design of an automatic and objective tool for detection and early prevention of frailty. In particular we have validated the proposed set of features comparing young healthy and older subjects and analyzed the correlation with the results of state of the art manual methods for frailty assessment. Future works will be devoted to in depth analysis of the proposed automatic tool in real screening campaigns and in the exploitation of the technique for smart living applications leveraging on the unobtrusiveness of the adopted sensor.

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