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Detecting and preventing falls with depth camera, tracking the body center

Amandine DUBOIS ^{a,1} and François CHARPILLET ^{b,2}

^a*Université de Lorraine, LORIA, Vandœuvre-lès-Nancy, France*

^b*Inria, Villers-lès-Nancy, France*

Abstract.

Fall is a major risk for elderly people. This paper is an outline of the research work that we are conducting in our group concerning the development of new technologies for fall detection and prevention at home. Our aim is to propose new affordable devices at home which: (1) automatically detect falls, and then alert whom is concern when a fall has been detected, (2) proceed with some measure in order to define an indicator associated with the risk of fall. Such devices could reassure persons affected by mobility problems or being recently injured in a fall, thus permitting them to stay at home longer. We are currently examining how low-cost RGB-D cameras could be used to track continuously a person at home. We show that we can easily extract, from depth images, the body center of mass of a person and some other simple parameters from which we can detect and prevent falls. Preliminary results are presented based on two real experimentations with young people, within an experimental smart home. 208 sequences were recorded for the first experimentation concerning fall detection and 106 strides were analyzed for gait parameters measurement.

Keywords. Detecting and preventing falls, Center of mass, Depth camera, Elderly people

Introduction

In the next decades, the population of elderly people will continue to grow. In France the number of people of more than 60 years old will increase by 10,4 million between 2007 and 2060 [3]. One third of elderly people at home fall each year [9] and this has motivated an increasing number of researchers to propose technological solutions to address fall detection and prevention. This is an important issue in order to permit people with autonomy loss to stay longer at home with satisfactory security.

Current fall detection systems are unsatisfactory because these systems are mainly based on sensors that the person must think to wear. We want to develop a system allowing to detect when a person falls and to call for help automatically. The aim is to avoid that the person stay a long time on the ground because some study showed that staying on the ground shortens life [11].

¹Université de Lorraine, LORIA, UMR 7503, Vandœuvre-lès-Nancy CEDEX, F-54506, France; E-mail: amandine.dubois at loria.fr.

²Inria, Villers-lès-Nancy, F-54600, France; E-mail: francois.charpillet at inria.fr.

The risk of falling for a person may be detected through some clinical tests such as timed up-and-go test [6], Berg test [2], Tinetti test, etc. But these tests are subjective and aren't applicable to everyone as for people having mobility problems or cognitive impairment [8]. Thus there is a real need to develop systems for objectively analyzing gait and for detecting mobility and balance. According to Auvinet et al [1], the irregularity of the lengths of steps is regarded as a relevant variable for the prediction of falls. Our aim is to develop a system allowing to analyze the evolution of gait parameters over time (in particular the lengths of steps) so as to be able to prevent eventual falls.

To develop a system able to detect and prevent falls we use a RGB-Depth camera, which has the advantage to be a low-cost sensor. We show that we can easily extract in real-time from RGB-D images, with a good accuracy, the center of mass of any person moving in the field of view of the camera. We also show that this parameter is an important feature to detect falls and to characterize the risk of fall.

We made the choice to include the detection of the falls in the more general context of activity recognition which consists in automatically determining the activity of a person over time. Our method uses the position and the velocity of the center of mass and the body shape of the person. For the prevention of falls, the lengths of steps of the person is estimated from the dynamics of the position of the center of mass on the vertical plane. In this work, we show that it is possible, from the center of mass, to detect the activity of the person, in particular to detect the falls, and also to measure the length of steps and thus to develop a tool to prevent the falls.

This paper is organized as follows. Section 1 is dedicated to a method for extracting the center of mass. Then, section 2 describes the system for detecting falls. Finally in section 3, we present a method for preventing falls.

1. Method for extracting the center of mass

In addition to the color image, the RGB-D camera provides a depth map allowing to reconstruct the real world 3D coordinates of all the points of the image. The first stage is to extract the background in order to extract the pixels corresponding to a moving person/object. We use a simple and fast method, the "running average" [5] method, which consists in learning the background by averaging over time the distances for each point of the depth map. At each time, the background distances are subtracted from the current distances to keep only mobile points. In Figure 2, in the top right-hand corner is the current depth image and in the top left-hand corner is the learnt background. Then we gather, with the method «Component labelling» [10], the mobile points belonging to a same object. In Figure 2, in the bottom left-hand corner the mobile points are represented in blue color. The displacement of the body can be analyzed by looking at the displacement of the center of mass as shown in Figure 1. In our system the center of mass is calculated by averaging all the mobile points of the person (geometric center of 3D mobile points). In Figure 2, in the bottom right-hand corner, the center of mass, obtained with the camera, is drawn on the vertical plane.

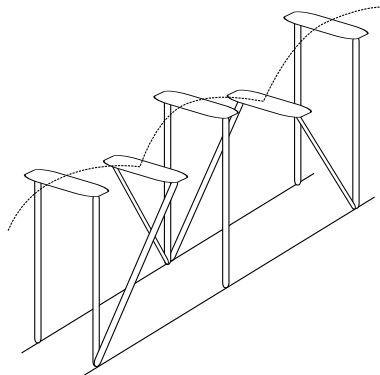


Figure 1. Vertical displacement of the center of mass.

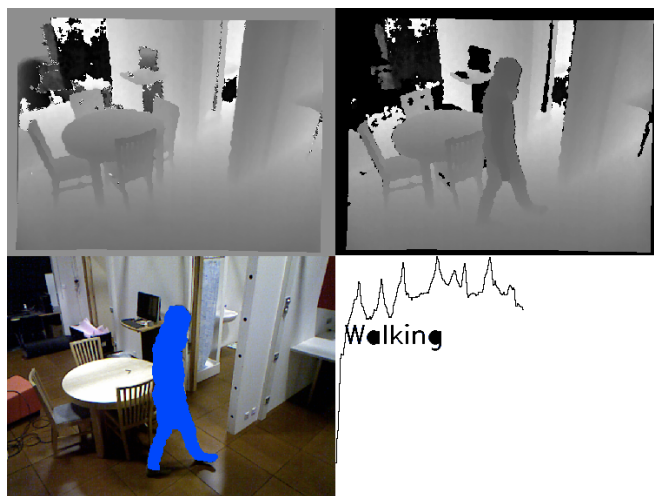


Figure 2. Center of mass extraction with RGB-D camera.

2. Detecting falls

The aim of this work is to discriminate falls among other activities such as sitting, lying on a couch... The approach is based on a Hidden Markov Model (HMM) [7], in which the behavior of a person is seen as a sequence of states over time, each state corresponding to one among eight activities of daily life: falling, walking (including the position upright), lying (on a bed, on a couch for example), sitting, lying down, squatting, going up on an obstacle (a chair, a footboard for example) and bending [4]. The center of mass of the person is the main observation for detecting in which state the person is, more precisely we use the vertical position and the vertical speed of the center of mass and the standard deviation of all the points belonging to the person. In Figure 3 we represent the trajectory of the center of mass for two activities, walking and sitting. The Forward-Backward algorithm [7] calculates the probability of being in each state at each time step. Twenty six healthy subjects performed eight activities and the model was trained with these eight situations from sixteen subjects which represented a learning database of 128 sequences.

We kept ten subjects, which represented 80 sequences, to test our model. The result is that each situation is recognized except "bending". There are no false positives except "sitting" and "squatting" which are detected instead of "bending". Falls are correctly detected except for one of them due to the fact that the subject rose immediately after he fell. Falls are detected without false positives. In Figure 2, the bottom right-hand corner is an example of decision taken by the algorithm detecting the state in which the person is.

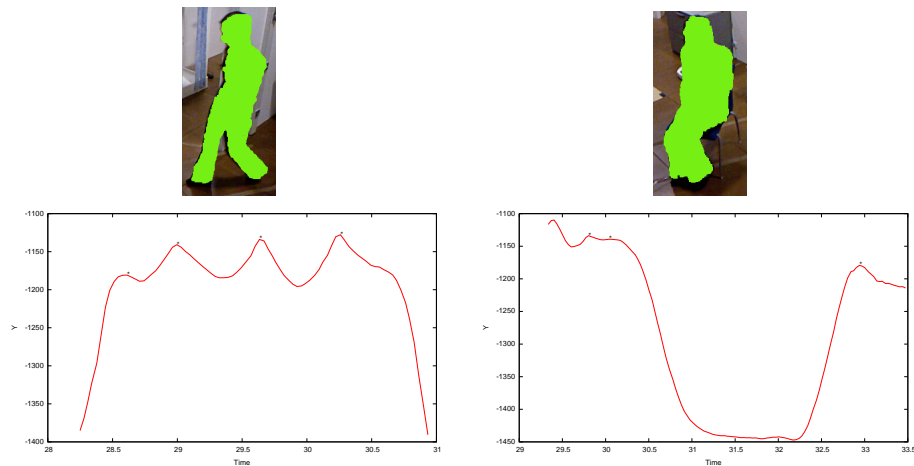


Figure 3. Tracking of the center of mass in two different activities

3. Preventing falls

As we said in introduction, the length of steps is clearly related to the degradation of the gait and it is a good indicator to evaluate the fall risk of a person. We extract this gait parameter from the vertical trajectory of the center of mass of the walking person. In Figure 4 the curve is an example of the center of mass trajectory for a walking person from which we extract the length of steps. This curve is then filtered by Kalman filter [7]. We define the length of steps as being the distance between two local maxima of the curve. We set up an experiment to validate the accuracy of the length of steps obtained with RGB-D camera. We placed pads soaked with ink under the tip and the back of shoes and several subjects walked on paper, marking it. This technique allows us to obtain the real length of steps, to be compared to the length of steps provided by the camera algorithm. Five subjects performed two situations, first the subject had to walk in a straight line normally and then he had to walk making small steps to better fit elderly people walk. The measured lengths were compared to the real lengths obtained with paper sheets. This comparison has been made on 106 lengths of steps, 39 normal steps and 67 small steps. The average error is 5.31cm for all steps, which represents an error of 11.78%. More precisely, we obtain for normal steps an average error of 6.38cm, which represents an error of 10%. For small steps, the average error is 4.69cm which represents an error of 12.80%. In order to correct a possible bias related to calibration issues we

performed a linear regression and defined a linear model of the error. After correction of the error, we obtained an average error for all steps of 3.14cm, which represents an error of 7% on the 106 lengths of steps. More precisely, for normal steps the average error is 3.98cm, which represents an error of 6.04%. For small steps, the average error is 2.73cm which represents an error of 7.55%.

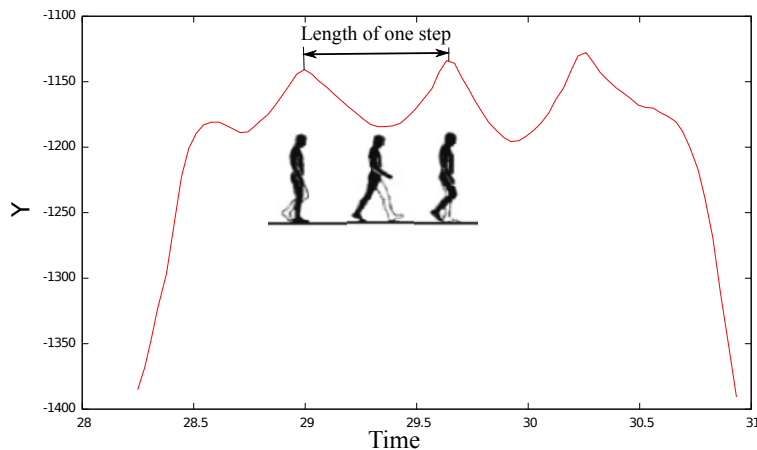


Figure 4. Lengths of steps extraction from the trajectory of the center of mass.

4. Conclusion

To conclude, we propose a simple low cost gait analyzer system. The system relies on a trained HMM. Good results for detecting and preventing falls have been obtained in laboratory conditions and since the model is independent of surroundings, we believe that it's general enough to work in other conditions. The next step is to deal with the problem of occlusions and to validate the approach in real living conditions either at home or in the physician office. Such a system is interesting to objectify the global analysis of elderly frailty at home or during physician examination.

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