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Machine learning based identification of elderly persons with cognitive impairment using dynamic time warping

Abstract: Cognitive changes in general occur with normal aging. This may lead to the prevalence and effect of age associated diseases. The understanding and identification of these age-related cognitive impairments is an important aspect in elderly population. This leads in the simple case, supporting a functional independence of the elderly and in a complex case, an early identification of dementia in advance. One important change with normal aging is the decline in gait functionality. The decline in gait is more visible in the elderly with more cognitive impairment during dual cognitive tasks, multi-tasking exercises. For the classification of the healthy elderly from the elderly having cognitive impairments, the gait data of the elderly is acquired through Kinect V2. A waking trial of 5m long is used to collect the gait data. 3D based pose estimation using the depth data is performed. Gait parameters and gait cycles of the individual elderly are estimated. In this paper, Dynamic Time Warping (DTW) algorithm is used to compare the patterns of the gait cycles of the individual in different trails such as Regular Gait 1 (RG1), Regular Gait 2 (RG2), Counting Backward 1 (CB1), Counting Backward 3 (CB3), Fast Gait (FG) and Words with Special Letters (WSPL). The identified cross levels along with the estimated gait parameters are used for training the machine learning algorithm. Support Vector Machines (SVM) were used for the classification of the elderly persons with or without cognitive impairments. The experiment results proved that such a classification of cognitive impairment levels using 3D pose estimation and machine learning helps in future for the identification of dementia in advance.

Keywords: Machine learning, dynamic time warping, cognitive impairments, classification, elderly persons.

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1 Introduction

Machine learning-based computer vision techniques are involved in many health applications in recent years. These include but are not limited to disease prediction, its diagnosis and corresponding suggestions for treatment. Many studies such as gait assessments and cognitive assessments have been performed separately in evaluating the health condition of elderly people. Increasing evidence from clinical practice, epidemiological studies, and clinical trials show that gait and cognition are inter-related in elderly people. The quantifiable alterations in gait among the elderly can be associated with falls, dementia or disability. Similarly, emerging evidences indicates that early disturbance in cognitive processes such as attention, executive function and working memory are associated with slower gait or gait instability during single and dual-task testing that leads to cognitive impairments. These evidences lead us to the prediction of future mobility loss and the progression to dementia.

In this paper a machine learning algorithm, namely Support Vector Machine (SVM) is used to classify healthy elderly and elderly with mild or severe cognitive impairments.

2 Related work

Changes in gait velocity and variability are not mutually exclusive. However, they provide different information. The work of [1] reported that gait variability during dual tasking predicted future falls among community living older adults during 2 years of follow-up, while gait velocity did not. The variability of several spatio-temporal gait parameters has been studied, with a stride to stride fluctuations in gait cycle timing (e.g. stride time) being the most widely reported [2]. Higher gait variability has been described in investigations with older adults with frailty [3], Parkinson's disease [4], in Alzheimer's disease [5] and are prospectively associated with a high risk of future falls and mobility decline [6].

There have been supervised or unsupervised machine learning approaches with features from gait analysis which classify elderly into different classes of cognitive impairments. The work of [7] proposed the use of SVM to classify a group of conditions in neurodegenerative diseases namely Amyotrophic Lateral Sclerosis, Parkinson's disease and Huntington's disease. These classification tries to distinct between healthy subject with respect to persons with some sort of neurodegenerative diseases. They are able to achieve good classification accuracies due to the use of some special feature selection approach from the available dataset. A Quadratic Bayesian classifier is used by [8] for the classification of the movement disorders in the elderly in relation to neurodegenerative diseases. [9] classified the people from the dataset into three stages of the neurogenerative diseases i.e. retro genesis, cognitive impairments, and gait disorders. They proposed the use of quadratic Bayes normal classifier. Elman's Recurrent Neural Network (ERNN) was used by [10] for the classification of healthy persons and persons with neurogenerative disorders.

Despite the mentioned techniques which were able to perform classification with good accuracies, the use of features from standard data sets is provided by PhysioNet or Neuro-Degenerative Disease Gait Dynamic Database (NDDGD) [11] [12]. Even though these datasets have different persons with neurodegenerative cases, they are very limited. The used data sets are quite old which means the techniques used for gait data acquisition can be outdated. In many cases, the database consists of persons with age including people from 54 years old. Several facts distinguish our approach from already existing. In our scenario, the gait data acquired from the people who are above 80 years of age. The generated feature set and gait parameters are subjected to the individual's requirements and are more specific in the identification of the cognitive impairments. Furthermore, we differ in terms of sensor technology and state of the art approaches for feature extraction.

3 System Architecture

In this chapter the architecture of the proposed approach is described. Gait data from elderly people is collected in a laboratory environment of Technical University Chemnitz by a Microsoft Kinect V2. From the acquired gait data, 3D pose of the individuals is extracted and the gait cycles and gait parameters are estimated. The estimated gait cycles for different trails are used by Dynamic Time Warping (DTW) algorithms and the DTW parameters along with the estimated gait parameters are given to the SVM for classification. The architecture of the system is shown in Figure 1.

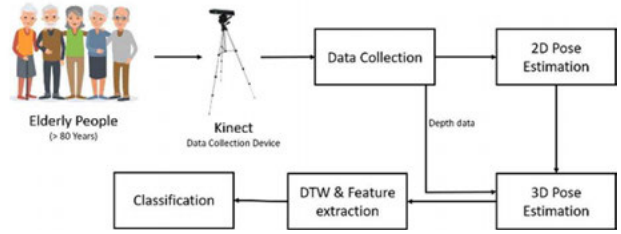

Figure 1: System architecture

3.1 Test persons

For the purpose of this study, gait data from elderly people who are above 80 years old is acquired. The participants are classified into three different groups based on the initial cohort study through Montreal Cognitive Assessment (MoCA) and Consortium to Establish a Registry for Alzheimer's Disease (CERAD). The groups are Cognitive Healthy Individuals (CHI), possible Mildly Cognitively Impaired persons (pMCI) and Mildly Cognitively Impaired persons (MCI). All test persons initially take part at cognitive (executive function tests), motor (gait analysis, balance tests), sensory (vibration perception threshold tests, proprioception tests) and neurophysiological (electroencephalograms) measurements. Depending on the time of participation, all measurements are repeated for a maximum of four times with an interval of eight months within the scope of three years project period to study the association of different changes over time. More than 250 elderly people's data is collected. All these measurements are performed with proper approvals and registered in German Clinical Trails Register DRKS00013167 [13]. The measurements are ongoing and will continue until the end of the project.

3.2 Data collection

The acquisition of gait data is performed by a Microsoft Kinect V2. Kinect is proven to be efficient in acquiring of gait data in an indoor environment without use of any wearable devices [14]. Kinect consists of three sensors, which is an RGB video camera with 20 frames per second, a depth sensor and a multi-array microphone. For the scope of this project, the data from RGB video camera and depth sensor data of each elderly is acquired. Each test person is supposed to walk in a specified path toward the camera and walk back in a walk trail of 6 meters. Different sorts of trails are performed during this data acquisition. The trails include Regular Gait 1 (RG1), Regular Gait 2 (RG2), Counting Backward 1 (CB1), Counting Backward 3 (CB3), Fast Gait (FG) and Words with Special Letters (WSPL). These trails bring some sort of distraction in human gait which are helpful in bringing the relationship with respect to their cognitive impairments. A more detailed information about the trails can be found in [15].

The RGB data acquired from the Kinect sensor is used to estimate the 2D pose. For the estimation of 2D pose, a technique based on Convolutional Neural Networks is applied [16]. This is pretrained on MPII, MSCOCO and COCO+Foot datasets. The acquired image sequences are cropped to the required size (512x424) and is used to estimate the 2D pose of the subject of interest. These acquired 2D poses consist of 25 key joints.

Based on the quality of the image, the identification of key joints may vary. Parallelly, the depth data acquired from the Kinect depth sensor is used to generate the 3D point cloud of the extracted 2D human pose. The 2D pose of the image is mapped with the acquired depth data to generate the 3D pose of the elderly person. This 3D pose is minimized to the selected key joints such as right-knee, left-knee, right-ankle, left-ankle, right-heel, left-heel for the purpose of the gait analysis.

3.3 DTW and feature extraction

The obtained 3D pose of the person as mentioned above in section 3.3, the coordinates of their ankles are obtained. These coordinates are extracted for every frame of the video sequence. From these ankle coordinates of right and left leg, the Euclidean distance in 3D-space between both feet are estimated for each frame.

DTW is a widely used algorithm to measure the similarity between the multi-variate time series data. In this paper we use DTW to monitor patterns of the distance between two feet for different trails of gait data.

The distance between two feet (gait cycle) of every test person for every trail were estimated. These trails need to be compared against each other. Let a two time series data for two trails (RG1 and CB3) are $X = (x_1, x_2, \ldots\ldots, x_n)$ and $Y = (y_1, y_2, \ldots\ldots, y_n)$.

The comparison of two vectors X and Y of the time series is defined as:

$$\boldsymbol{D : f \, X \, f \, \square \, R \, \square \, 0} \tag{1}$$

Where,

$$\boldsymbol{x_n, y_n \in f \; for \; n \in [1, n]} \tag{2}$$

The function (1) is used to calculate the lowest distance measure between X and Y. For this dynamic programming theory is used to compute the distance measure to each cost vector C_n. The cost vector C_n is the sum of absolute differences of x_n, y_n [17] [18]. The Result of DTW is the distance D from X and Y which is considered as a feature. Similarly, from 15 trails, different features are extracted. These set of features are used in our work for the classification of the health status of elderly people.

3.4 Classification

For the purpose of classifying elderly people, machine learning algorithm SVM is used. SVM's are supervised machine learning algorithm that is mostly used for classification. In SVM, the data item is placed as a point in n-dimensional space. For the purpose of classification, a hyper-plane that differentiates the two classes needs to be identified. As mentioned earlier, we are interested in classifying the subjects in three groups: CHI, pMCI and MCI. The DTW temporal features are considered as inputs to the SVM. We consider one multiclass classification, which is CHI vs pMCI vs MCI and three binary classifications, namely CHI vs pMCI, CHI vs MCI, CHI vs pMCI + MCI.

Table 1: Classification results of different cognitive status of elderly.

Classification	Acc	Precision	Recall	F1-Score
CHI vs PMCI vs MCI	52	48	92	63
CHI vs pMCI	55	93	65	74
CHI vs MCI	69	67	98	80
CHI vs pMCI + MCI	61	60	83	65

In total, 142 elderly people's data is used for initial tests. Their gait data for RG1, RG2, CG1, CG3, FG, WSPL were used for the analysis. The classification results along with the performance metric for each problem with the extracted DTW features are presented in Table 1.

The low overall accuracy highlights the need for a more number of features and more person's data. Despite the overall accuracy is low, SVM is able to identify the individual classes CHI (accuracy 87.3 %), pMCI (accuracy 74.6 %) and MCI (accuracy 84.4 %) individually with higher accuracies. Despite such accuracies for individual classes in different combinations, the overall accuracy is low due to high false positive rate. This may be due to the fact that pMCI and MCI seems to have more common relations and similarly for certain persons, it is hard to find a clear distinction in gait between

CHI and pMCI persons. As all the test persons are above 80 years old, their gait patterns have similar characteristics. Finally, machine learning techniques are feasible in the classification of cognitive impairments from healthy persons and can support in the future for early detection of dementia.

4 Conclusion

Analysis of gait is an important characteristic to assess the state of cognitive impairments of elderly people. In this paper, we used SVM to classify the CHI, pMCI and MCI and achieved a moderate accuracy of classifying the individual classes ranging from 74.6 % - 87.3 %. In order to find the most valuable temporal gait features, the DTW algorithm is used to align extracted features from the distance between two feet of the persons for RG1, RG2, CB1, CB3, FG, and WSPL trails. The results demonstrate that these features play a crucial role in the classification purpose but may not be sufficient. In the future, other temporal gait parameters (stride time, step time) and gait parameters (stride length, step length) and statistic parameters such as persons age, shoe size and height will be considered as feature set for classification. As the acquisition of gait data is still in progress, in the future, the comparison of gait behaviour at differentiate intervals needs to be evaluated and a possible shift of persons from CHI to pMCI or MCI needs to be identified.

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