Motion analysis of Mild Cognitive Impairment patients using accelerometer

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Abstract

Mild Cognitive Impairment (MCI) is a brain function syndrome that involves mild cognitive deficit which is beyond what would be expected for normal aging but not serious enough to cause dementia. MCI patients are prone to Alzheimer's disease or other forms of dementia. Current MCI diagnosis involves extensive clinical judgement which often includes close clinical observation. Such observation is both laborious and time-consuming. We propose to use motion analysis based on the acceleration data collected during the laboratory assessments to help identify potential tasks that are more error-prone, thus facilitate the clinical assessment process. Clinical observations suggest that MCI patients tend to pause more often than normal people when perform certain tasks, since memory loss is a predominant symptom and the patients have difficulty recall things. Their thought process in determining what to do next is also slower than normal people and tend to make mistakes more frequently. These characteristics lead to more direction changes in motions. In our study of MCI patients' hand movement patterns, we found more pauses and direction changes compared to normal people. We believe these findings open up new opportunities for future research on MCI diagnosis.

Introduction

MCI is an intermediate stage of brain malfunction between normal aging and more serious dementia, of which the most common one is Alzheimer's disease. Current diagnosis relies heavily on clinical observations which is usually time-consuming. Effective computer aided MCI classification therefore is much desired in facilitate the diagnosis process.
Body motion detection using accelerometers has drawn considerable attention as an alternative of visual information based movement recognition. With accelerometers, we can collect motion data including azimuth, pitch, roll, and acceleration along x, y and z rotation vectors of the device. Different patterns of movements yield different results, it's thus logically possible to reversely calculate the corresponding motion based on the given acceleration data.
The clinical observations are based on recorded videos of patients preparing breakfast, lunch, etc. in prearranged environment settings. Experts then examine the videos closely to find abnormal MCI suggestive behaviors. This process can be greatly facilitated if we can collect data that contains information about the patient's movement patterns and have them analyzed automatically with a computer program. The most distinguishable features from the clinical observations are pauses and sudden moves. During the laboratory assessments, the patients wear a smartwatch that collects acceleration data. We then feed the data into our classification algorithms to analyze if there are suspicious movement patterns such as more pauses and direction changes. The results of our analysis suggest that MCI patients pause and change

directions more often based on the patterns of their hand movements. Certain subtasks are complicated and require more attention than other tasks, and MCI patients are prone to make more mistakes that resulting in more direction changes and pauses that can be reflected from the acceleration data. Some of these subtasks are identified in our study and we believe the research is beneficial in cutting down the time and resources put into clinical MCI diagnosis.
The diagnosis of MCI is by far largely clinical based on a doctor's professional judgement. A doctor typically needs to examine the patient's detailed medical history for any previous medical conditions or family history of memory problems or dementia. This is combined with brief tests that assess mental status and neurological conditions. Sometimes laboratory tests such as blood tests and neuroimaging are performed as ancillary testing to further assess a patient's cognitive conditions. Since neuropsychological tests are an important part of MCI diagnosis, it's desirable that the tests results can be automatically analyzed by a computer. As an initial exploration, our goal in this study is to find the difference of movement patterns between MCI patients and normal people, thus providing more clues that leads to successful MCI diagnosis.

Data collection and preprocessing

Studies have shown that the occurrence of MCI is very rare, with a ratio of less than 7.2% per 100 non-demented persons.[3] Understandably MCI patients are very difficult to find, we therefore used data collected from participants who imitate MCI patients. Our participants constitute 18 young adults for each group: MCI patients and normal people. They imitate MCI patients by entering a mentally equivalent status after purposely getting distracted.[8]
All the data are from clinical tests. They are collected using a smartwatch our subjects wear on their wrists. The tests are designed specially to test the subjects' cognitive capabilities. Table 1 below shows a sample subset of the data:

time	index	Acceleration X	Acceleration Y	Acceleration Z	Subtask
13:52:38	352	-3.8630445	-0.6027403	8.025514	select jelly
13:52:38	353	-2.754529	-0.29388827	8.698284	select jelly
13:52:39	354	-2.754529	-0.29388827	8.698284	move jelly
13:52:39	355	-3.6475663	-1.7040731	10.125229	move jelly
13:52:39	356	-3.6475663	-1.7040731	10.125229	move jelly

Table 1 Acceleration data sample of an adult subject preparing a lunch

The data are trimmed to remove data segments with missing labels or out of assessment time frames. Some subtasks are omitted by our participants during the assessment and data pertaining to those tasks were removed for convenient analysis, since we're only interested in the subtasks we can compare across different subjects.

Since MCI causes short-term memory losses, the patients sometimes have difficulty remember things and tend to hesitate more often than normal people when making decisions. We believe that MCI patients make more pauses during our tests, which is also consistent with our observations on the recorded video for the tests. Since the patients' hand movements are directly reflective on the collected acceleration data, from which we can extract important pause information.

The accelerometer collects data along the X, Y and Z directions. X and Y are both tangential to the ground at the device's current location and points approximately East and North, respectively. Z is perpendicular to the ground plane and points to the sky. [1] During data preprocessing, gravity component is removed so that the data can more closely reflect the physical movement of interest. We then compute a normalized magnitude:

$$M_i = \sqrt{{x_i}^2 + {y_i}^2 + {z_i}^2}$$

The accelerometer sensor in the smartwatch measures the force applied to the sensor itself (**Fs**) using the relation [2]:

$$\mathrm{Ad} = -\sum \mathrm{Fs} \,/\, \mathrm{mass}$$

The measured acceleration is influenced by the gravity:

$$\mathrm{Ad} = -\mathrm{g} - \sum \mathrm{F} \,/\, \mathrm{mass}$$

As can be seen in Table 1, the acceleration component Z has significantly larger values than X and Y due to gravity. To remove this gravity component, we used a low pass filter.

It would be straightforward to think that since after all we're using acceleration, we would be able to obtain the real time spatial trajectory by doing a double integral on all three components. However, errors will occur in numerical integration because the process is only approximating the underlying continuous signal to be integrated.[3,4] The integration of noise introduces a root mean square value that increases with time, even when the accelerometer has no motion.[3]

Motion analysis

Significant attention has been attracted in using acceleration data for motion analysis. [5,6,7] At the current stage, the motion analysis is performed primarily to identify certain subtasks that are better indicator of MCI. We expect that by refining our motion analysis algorithms, we can use it to classify acceleration data directly to diagnosis MCI in the future.

1. Pauses

To identify pauses, we count the consecutive number of data points with magnitude less than a threshold. A number less than the predefined window size *w* will constitute a pause. We consider the fact that the body movement for different individuals have different pace and speed, so we compute the threshold by calculating the average magnitude as well as the standard deviation instead of using a fixed value. Out test is designed to contain a "select quit" session, which allows us to separately observe and calculate the subject's usual pace of movement, that is, we calculate the magnitude standard deviation (*sd*) and the average magnitude (*ave*) based on this session. The threshold t is obtained by the following:

$$t = ave + n \times sd$$

where n is a parameter to be tuned. A magnitude less than t is considered in pause phase. If a consecutive number w of acceleration data points with $M_i \leq t$ is found, we consider it a pause. Figure 1 below shows how tuning the parameters n and window size can affect the result of pauses analysis. On the horizontal plane, the horizontal axis is the number of standard deviation, while the vertical axis is the window size, namely the number of consecutive acceleration data points with magnitude below the threshold t. The vertical axis in the vertical plane is the ratio of average number of pauses per subtask from distracted adults (MCI) to that from undisturbed adults (healthy).

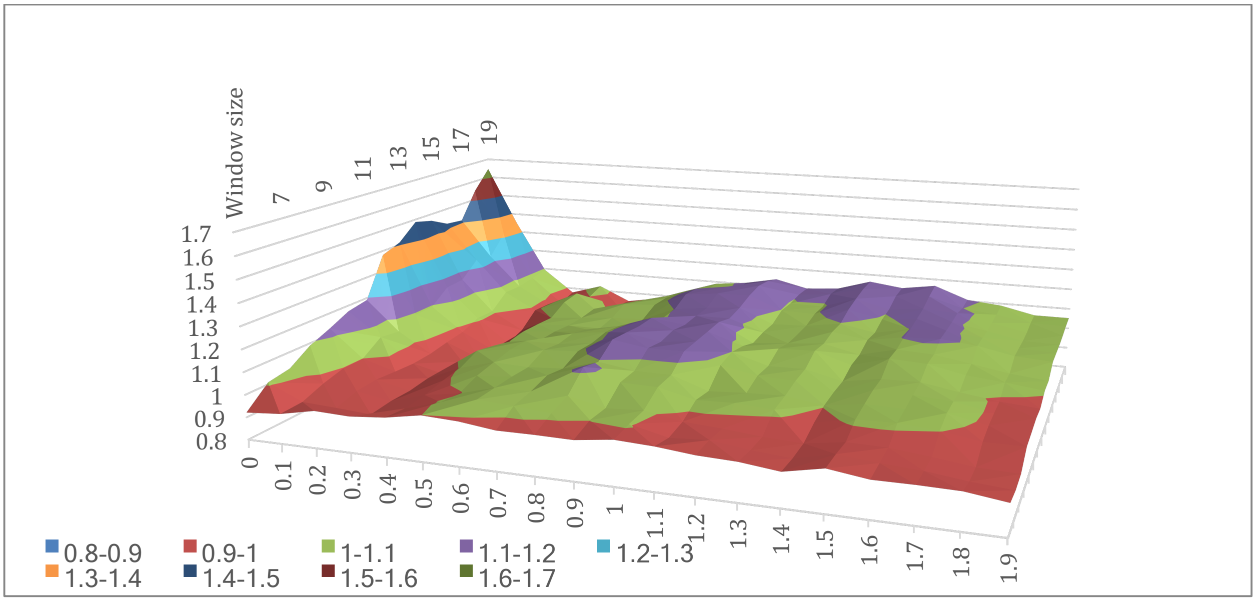

Figure 1. Interplay of parameters on the result pauses number comparison between patients and normal people

Since we're looking for larger number of pauses on MCI patients compared to healthy people, our region of interest lies on the mountains of the 3D surface graph, where the ratio on the number of pauses is at the maxium. As we can observe from Figure 1, a larger w and a smaller n yields more distinguishable pause numbers on the MCI patients and normal people. However, each subtask has a limited duration which puts an upper bound onto the window size. We select our ideal window size as 15 to balance the pause detection performance and the subtask duration limit. Thus, we use n = 0 and w = 15 for our pause analysis.

2. Direction changes

We consider the number of direction changes along all three directions and then calculate the average number of changes per second for each activity. Whenever there is a direction change, the acceleration changes sign from positive to negative or from negative to positive. To prevent the noise from obscuring the result, we only take the peaks [Figure 3] into consideration. By carefully select the thresholds, we can target only the significant peaks while discarding negligible ones. We calculate direction changes on all three arises and use the average for our analysis.

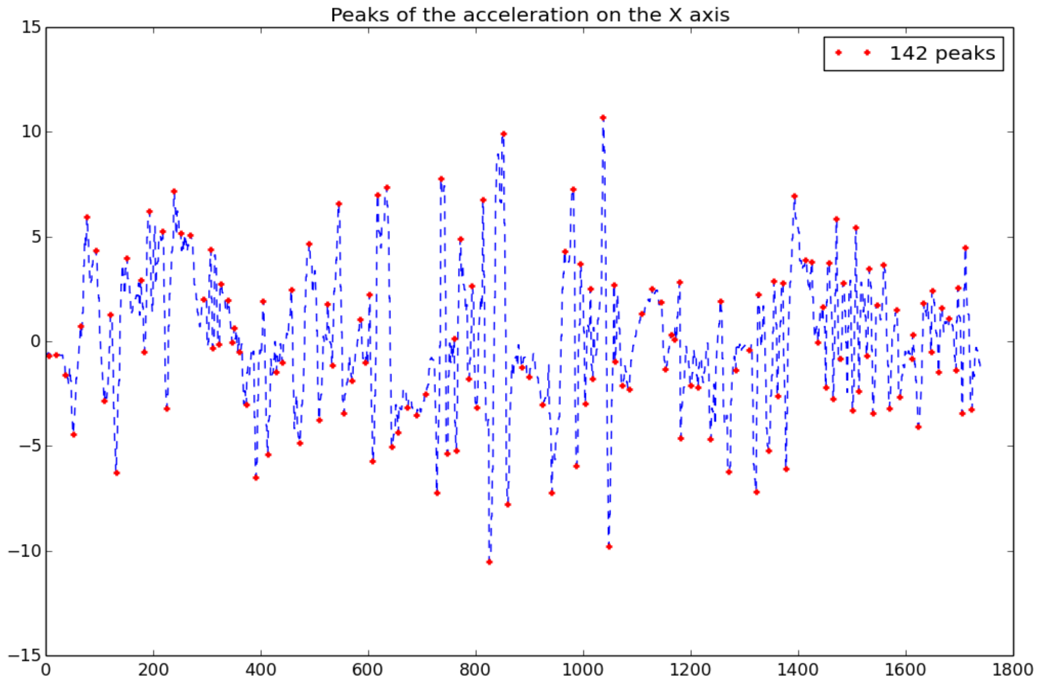

Figure 3 Peaks on the x-axis acceleration data. The horizontal axis is the index and the vertical axis is the magnitude.

For direction changes measurement, we used the function peakutils.peak.indexes(y, thres, min_dist) to obtain the peak positions, where y is the 1D amplitude acceleration data along each of the x, y, and z axis, thres is the normalized threshold, and min_dist(int) is the minimum distance between each detected peak. Whenever a peak's sign is opposite from the previous one, e.g., changing from positive to negative or positive to negative, the number of direction changes is incremented.

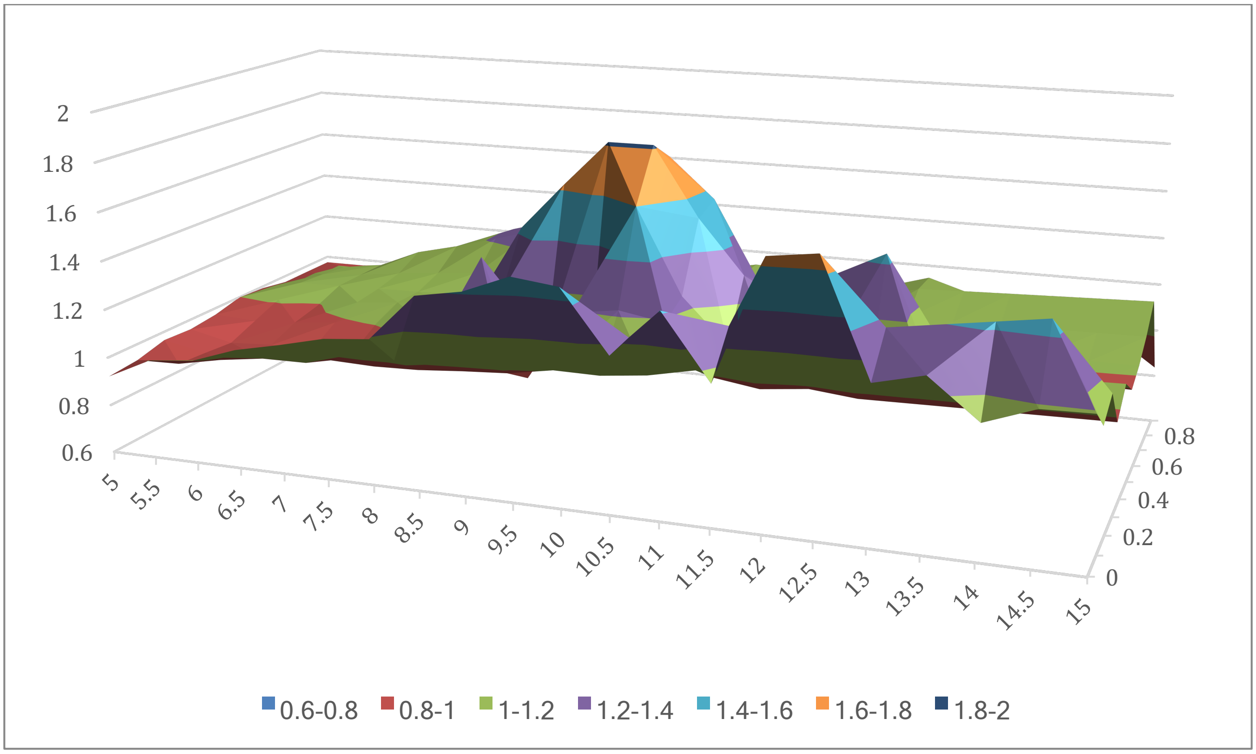

Figure 4 Effect of different parameters on the number of direction changes ratio.

In the horizontal plane, the horizontal axis is the min_dist, while the vertical one is the thres. The vertical axis in the vertical plane is the ratio between the average number of direction changes of all subtasks of distracted adults versus undisturbed adults.
From Figure 4 we can observe that the best parameters can be obtained from the middle of the graph. The ideal parameter is min_dist = 10.5 and thres = 0.5.

Results and Analysis

1. Number of pauses

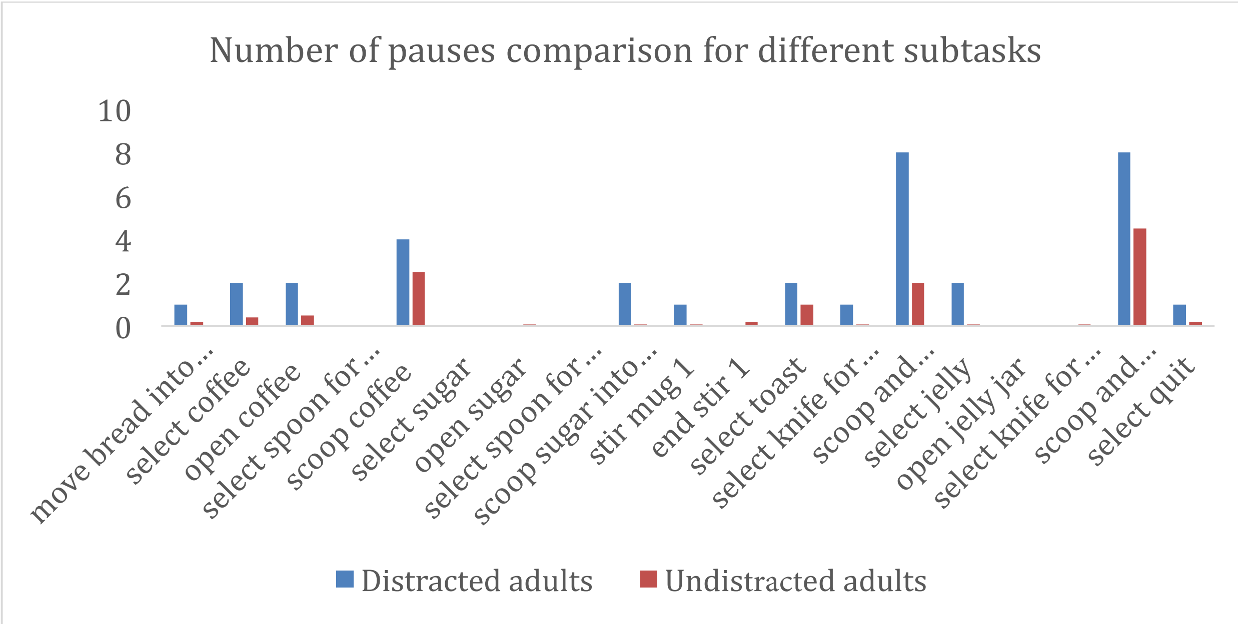

Figure 5. A comparison of number of pauses between distracted adults and undisturbed adults with n = 0 and w = 15.

The above figure shows the number of pauses comparison after we used refined parameters. The number of pauses differs significantly between that of distracted adults and undisturbed adults. It's evidential that pauses are an effective factor to look into in MCI diagnosis. Also, subtasks that show a sharp comparison between number of pauses from distracted adults and those from undisturbed people, such as "scoop and spread butter", can be used as "marker" subtasks to facilitate lab assessment.

2. Number of direction changes

Although the results from distracted adults and undisturbed adults is not in as sharp comparison with each other as in the case of number of pauses, we can still see that for most of the subtasks, there are more direction changes from distracted adults. Subtasks such as "scoop and spread jelly", and "scoop sugar into mug" are also good indicator to be chosen to facilitate laboratory assessment of MCI.

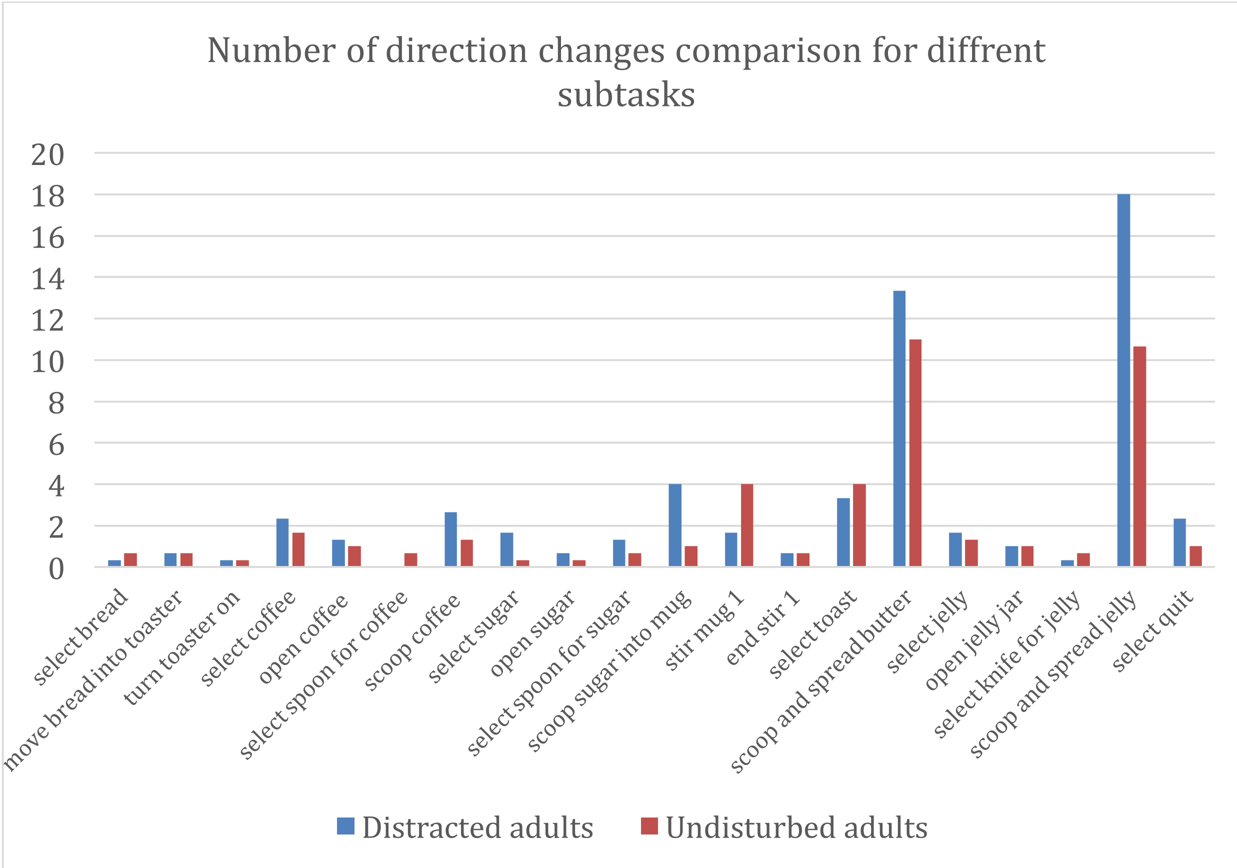

Figure 6 A comparison of number of direction changes in different subtasks between distracted adults and undisturbed adults with min_dist = 10.5 and thres = 0.5.

Conclusions

In this research, we have investigated using acceleration data analysis to recognize motions. The results illustrate that certain subtasks are indicative of MCI mental issues. This can be helpful for initial scan of the clinical MCI assessment, since doctors can have the options of looking at a few subtasks first, instead of having to go through subtask detail. The approach of using number of pauses and direction changes is successful in roughly classing MCI prone people from healthy adults. If more data is collected in the future, the problem can be further analyzed with machine learning algorithm to provide further insights into facilitating laborious clinical MCI assessment.

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