CLASSIFICATION AND CLUSTERING OF BRAIN INJURIES FROM MOTION DATA OF PATIENTS IN A VIRTUAL REALITY ENVIRONMENT

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Abstract: Virtual Reality (VR) has been found to be an effective rehabilitation tool for brain injury patients. We show that motion data from these VR sessions can be effectively used to both cluster and classify patients according to types of injury. Neural Network and other tools were used to differentially classify patients with traumatic brain injury, cerebral vascular accident (stroke) with and without spatial neglect and healthy individuals solely from the motion data. Clustering techniques also successfully duplicated the classification division. These results have potential implications for scientific research, automated diagnosis and integrated individually adaptive therapies in the virtual reality technology.

1 INTRODUCTION

1.1 Background

Recent advances in computer science and engineering have allowed scientists and clinicians to introduce virtual reality (VR) technology to various medical fields in general, and to rehabilitation in particular. Virtual reality applications let patients function in simulated environments where they are safe on one side, but practice real-world functions on the other side (see review at Weiss et al., 2006) . For example, a stroke patient may practice virtual street crossing in the clinic before trying to cross a street in the physical world (Kats et al., 2005). Beyond the ecological validity offered by virtual environments, they are also carefully controlled so they can be standardized, and the behavior of the patients is monitored and recorded. The collected data can be analyzed and used for clinical diagnosis or progress evaluation as well as general scientific research. However, as virtual reality platforms produce very large amounts of data, many researchers end up reducing the analysis to simple outcome measures such as reaction time, accuracy level etc.

We propose that such patient data are prime candidates for analysis using machine learning tools. This study aims to explore how various approaches may be used for analysis of patient data under constraints posed by the clinical conditions. For our proof of concept we focused at brain injuries, and in particular at the population of CerebroVascular Accident (Stroke) patients.

A stroke is a lesion of the brain resulting from a disturbance in the blood supply to the brain, due to obstruction or rupture of a blood vessel. Stroke causes a neurological deficit which may lead to various types of disabilities such as cognitive, emotional and motor impairments. In some cases stroke leads to spatial neglect. Patients with neglect are impaired in directing attention to selective part of space, usually the half of space that is opposite the injured hemisphere, and are unaware of their deficit (Robertson and Halligan, 1999). Neglect is commonly assessed using paper-and-pencil tests. However, these tests have several substantial drawbacks that often lead to a misdiagnosis of less

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severe cases. For example, a stroke patient who had passed the traditional tests and even got back his driver license, yet experienced multiple car accidents which occurred due to lack of attention and awareness to the neglected visual hemifield (Deouell, Sacher and Soroker, 2005). Other studies have also shown the weakness of conventional tests in neglect, and the potential of using virtual reality technology for accurate assessment of this neurological condition (Dvorkin et al., 2008).

Several types of VR methods are used for the investigation and treatment of stroke. The main one we used for this study implements a 3D environment, where the patient has to reach and "touch" a virtual ball appearing at various spatial locations (see Figure 1). Each reaching trial produces a data vector which includes the x,y,z coordinates and orientations (6 degrees of freedom) of the moving hand at 60 Hz sampling rate.

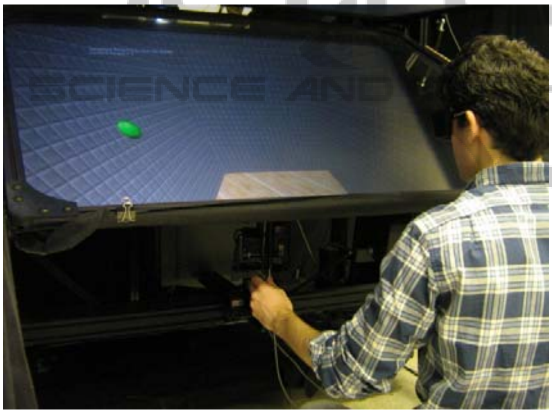

Figure 1: The VRROOM 3D platform.

Beyond the 3D experiment we also used machine learning tools in order to analyze data gathered by a 2D VR system, where subjects perform virtual shopping. In this additional experiment we implemented learning tools in a more challenging virtual environment. In this VR application the data is only two-dimensional and also is very noisy. Finally, in this experiment we included traumatic brain injury (TBI) participants, which constitute another common patient population.

In analyzing the data produced by these VR platforms, we had to overcome several hurdles. First and foremost, the sample size in these studies is quite small for technical and clinical reasons. More ever, as the participants get tired with time, the length of each experimental session is rather limited. Thus we had to find ways to process noisy and scarce data. These issues will be addressed later on. As even simple human motor performance is quite challenging for meaningful analysis, we approached this challenge using two levels of classifications as each one may yield a solution for a different problem.

Two-class classification: This approach may be quite valuable when it comes to differential diagnosis (DD). Several types of brain lesions may produce very similar performance, not always easily clear even to a professional eye. Thus it would be of clinical benefit to detect which of the suspected conditions the patient suffers from. After training on some clear cut cases, a neural network may generalize and classify the more questionable cases.

Zero-class classification (clustering): Clustering techniques lend themselves for analysis of heterogeneous populations, like stroke patients. Since no two stroke patients are identical, clustering them into subclasses leads to better classification than the coarse ones used today, i.e., mild, severe, and so forth.

1.2 Contribution of Study

We believe that finding the appropriate way to harness machine learning to analysis of human behavior has a significant potential to better understanding of brain injuries. These injuries manifest themselves in such a wide spectrum, so patients may suffer from inaccurate evaluation of their condition. Also, better analysis of movement patterns may greatly assist neuroscientists in their pursuit of better understanding of brain mechanisms such as perception, attention, motor planning and control.

In the following sections we shall demonstrate the feasibility of these approaches suggesting the relevance of machine learning tools.

2 METHODS

2.1 3D Experiment

Population: 29 volunteers participated in this study. Ten of them were diagnosed as suffering from stroke without clinical signs for neglect, nine suffered stroke and showed signs for neglect. The other ten were healthy adults in similar ages. The patients were diagnosed as having different levels of severity of their medical condition, ranging from mild to severe.

Procedure: Participants were positioned in front of the VRROOM (Virtual Reality and Robotics Optical

Operations Machine) system, shown in Figure 1 (Patton et al., 2006). On each trial a virtual target appeared randomly in space in one of 49 possible positions. Participants were instructed to reach toward the target as soon as they detected a target appearing within the scene, using their unimpaired arm. Each subject was presented with 343 target stimuli altogether.

Analysis: The data vectors were first preprocessed in order to eliminate pre-mature movement initiations or omissions (i.e., when the subject did not respond within three seconds). Also, any hand movement prior to the stimulus appearance was ignored as it is not part of the experiment.

The input vectors were of **several types**:

- Long Vectors - including the data from the onset of the target stimulus in the virtual environment till the end of the hand movement.
- Movement Vectors – consisting of data from the response of the subject, i.e., only from the moment the subject started a physical response.
- Initial/final Vectors – These vectors included the initial/final 130 data points of the movement. As oppose to the former types, these vectors were of fixed lengths.

Cross-validation: Two subjects of each group were removed during the training session. They were used for testing of the generalization. This was repeated 18 times and percent of successful classifications was calculated.

2.2 2D Experiment

Population: 99 volunteers participated in this study. 54 were healthy adults, 11 adults who suffered from CVA (without neglect), 9 children suffering from TBI and 25 healthy children.

Procedure: A virtual supermarket was presented to the participants using the GestureXtreme platform (`www.GestureTek.com`). This system is based on video motion capture technology where user is captured by video camera and sees his image in immersive 2D VR environment on the screen (Figure 2). Motion tracking algorithm produces two-dimensional coordinates of the user's movements. The participants were instructed to touch certain virtual products according to a shopping list (Rand et al., 2004).

Analysis: The data vectors were first preprocessed in order to find least noisy segments where the movements of the hand are consistent over a period of several seconds. At a rate of 15 frames per seconds, a typical segment consisted of several coherent chunks of 7-10 second durations. Thus each participant produced eventually about 750 data points (x,y,t) of his hand.

The noisy and fragmented nature of the data prevented us from creating input vector of whole movements or even long segments. Thus the input vectors were short and of fixed length of five data points. The cross-validation was similar to that used in the 3D experiment.

Figure 2: A sample view of a subject within a GestureXtreme virtual environment.

2.3 Architecture and Training

2.3.1 Two-Class

2D Experiment: For this experiment we used a feed forward network architecture with one hidden layer, which received as input a 15 element vector – 5 consecutive hand movements vectors (x,y,t). The hidden layer had 5 elements. All together an architecture of 15-5-1. For the more difficult case (TBI v. CVA) a network of the structure 15-20-10-1 (2 hidden layers) was applied.

3D Experiment: Here we used the same feed forward network architecture with a different input layer, 1400 elements for a long vector (1400-5-1), 1000 elements for a movement vector (1000-5-1), 130 elements for initial/final vectors (130-5-1).

In both experiments the training method was Levenberg-Marquardt initially. Later we discovered that the resilient back-propagation algorithm obtains the same stable results only with a much faster processing time.

As the difficulty increased the number of epochs increased as well, from 50 to 300 epochs.

2.3.2 Zero-Class

For both of these experiments we used a Kohonen Self Organizational Map (SOM) network. The topology we have chosen was that of a line with 7 clusters. Training was 50 epochs.

3 RESULTS

3.1 Terminology

When describing the results in text and tables there are four main populations whose subjects may be referred to by a combination of letter and number:

- Healthy participants are denoted as H. In the 2D experiment HA represent healthy adults and HC represents healthy children.
- Stroke (a.k.a. CVA) who were not diagnosed as suffering from neglect are denoted as S.
- Stroke patients who are also suffer from neglect are denoted as N.
- People with traumatic brain injury (TBI) are denoted as T.

3.2 Two-Class

3.2.1 3D Experiment

As seen in Table 1 the success rates in classification of long vectors were above chance level. The neural network was successful in generalizing in 82-97% of the time. It is not surprising to see that the best rate was achieved for the Healthy/Neglect classification, for neglect is a condition which tends to be explicitly manifested. From a clinical point of view the distinction between neglect and CVA is (82%) is certainly more meaningful, since traditional assessments often lead to a misdiagnosis of less severe cases of neglect.

As explained earlier, long vectors include all data from the onset of the target stimulus till the end of the hand movement. This includes the target detection as well as both movement planning and execution. Thus the distinction between different populations may be the result of a cognitive perceptual component, (i.e., reflecting the target detection latency of response phases), or a motor component. Such evidence has of course a scientific merit but it does not require a neural network to measure response time.

While there is ample evidence for a perceptual deficit associated with neglect, motor control studies have produced a large amount of contradictory data.

Hence we also attempted to perform a 2-class classification using movement vectors. In this case the input included only data from moment initiation till the end of the movement.

Furthermore, as neglect, almost by definition, manifests itself in one half of the visual field, we chose to use only the relevant hemi-field in the input data.

The classification results resemble very much the ones produced with the long vectors, ranging from 81% to 100%. This implies that the distinction between the populations manifests itself in more complicated ways than reaction time.

In order to further investigate the differences between these populations, we used another length of input. This was done by preparing a vector consisting of either the initial or the final movement segment (length of 130 data points). This approach may assist in focusing the research to the critical point of the hand trajectory, where the difference may lie.

Table 1: Success rates of 2-class classification in 3D data.

Vector size	Populations	BP NN Average Success
Long	Healthy/CVA	86%
Long	Healthy/Neglect	97%
Long	Neglect/CVA	82%
Movement	Healthy/CVA	83%
Movement	Healthy/Neglect	100%
Movement	Neglect/CVA	81%
Initial segment	Healthy/CVA	69%
Initial segment	Healthy/Neglect	81%
Initial segment	Neglect/CVA	89%
Final segment	Healthy/CVA	83%
Final segment	Healthy/Neglect	89%
Final segment	Neglect/CVA	69%

The classification results are not all that decisive in general, ranging from 69% to 89%. However, when comparing the success level of the classifications, it seems that it was easier for the NN to classify healthy from CVA or from neglect in the final segment, compared to the initial segment (83% vs. 69% and 89% vs. 81% respectively). On the other hand, the more challenging classification, the one between CVA and neglect patients seems to be more distinct in the initial segment (89%) rather than the final segment (69%).

It should be noted that the key findings of this analysis were also reproduced using SVM.

3.2.2 2D Experiment

Compared to the previous VR system, this platform produced very noisy data, thus the preprocessing reduced the inputs to short vectors each one covering about 750 data points.

The results, appearing in Table 2, indicate that the NN had high success (90%-100%) rates in comparing the three populations who participated in this experiment, namely healthy, CVA and traumatic brain injury. It is interesting to mention that in the CVA group there was a patient who was consistently misclassified as healthy even when his data was the training phase. Reviewing closely his medical files revealed that this particular patient indeed suffered from CVA but he had only cognitive impairments but no physical disability. This anecdote, beyond demonstrating the clinical potential of the system, suggests that the NN classified according to movement features of the subjects' behavior rather than by cognitive or attributes.

Table 2: Success rates of 2-class classification in 2D data.

Vector size	Populations	BP NN Average Success
5 data points	Healthy/CVA	90%
5 data points	Healthy/TBI	100%
5 data points	TBI/CVA	97%
5 data points	Healthy Adults/ Healthy Children	50%

Since the TBI patients were all much younger than the CVA patients, we suspected that perhaps it is the age difference that accounts for the classification between these populations, rather than the clinical condition. Hence we tried to classify the healthy children from the healthy adults. As seen in Table 2, the classification failed (50%), so it appears that age did not play a role in the CVA/TBI classification.

3.3 Zero-class

3.3.1 3D Experiment

Stroke causes a wide array of damages leading to many types of medical conditions. Some of these sub-categories have received a distinctive title, such as neglect. Yet the definitions are rather broad, and the cut-off points are not so accurate. In this phase of the study we picked various subsets of the patients and divided them into groups using clustering tools. Following this, the patients' medical records were examined in order to test the clinical validity of these clusters, and whether they point to meaningful directions. We chose various population types, and employed the Kohonen algorithm to cluster them to 2, 3 or 7 clusters. The main results appear in Table 3.

First we were interested in finding out how homogenous our healthy control group is by itself. Most of the healthy subjects were clustered into two neighboring clusters. One subject however, referred to as H10, was clustered all by his own, for unclear reasons.

The CVA population by itself appeared to be

Table 3: Clusters produced for 3D data.

Vector size, Populations, (Num. of clusters allowed)	Kohonen Clusters
Movement, Healthy, (7)	3: H01,H02,H04,H06,H08 4: H03,H05,H07,H09 6: H10
Movement, CVA, (3)	S01-S10
Movement, Neglect, (2)	1: N03,N04,N06,N07,N9 2: N01,N02,N05,N08
Movement, Healthy/CVA, (2)	1: H01-H09,S04,S08 2: S01,S10,S02,S03,S05,S06,S07,S09
Movement, Healthy/Neglect, (3)	1: N03,N04,N06,N07,N09 2: N01,N02,N05,N08 3: H01-H09
Movement, Neglect/CVA, (2)	1: N01,N02,N03,N04,N06,N07,N09 2: S01-S10,N05,N08
Movement, All, (3)	1: N03,N04,N06,N07,N09 2: H05,H09,N01,N02,N05,N08,S01-S10 3: H01,H02,H03,H04,H06,H07,H08
Initial segment, Healthy/CVA, (2)	1: H01,H02,H05,H07,H08, H09,S01,S06,S08,S09 2: H03,H04,H06,S02, S03,S04,S05,S07,S10
Initial segment, Healthy/Neglect, (2)	1: H01-H09,N01,N02,N04,N05,N08 2: N03,N06,N07,N09
Initial segment, Neglect/CVA, (2)	1: N03,N06,N07,N09 2: S01-S10,N01,N02,N04,N05,N08
Initial segment, All, (2)	1: H01-H09,N01,N02, N04,N05,N08,S01-S10 2:,N03,N06,N07,N09
Final segment, Healthy/CVA, (2)	1: H01-H04,H06-H09,S01,S02,S04-S10 2: H05,S03
Final segment, Healthy/Neglect, (2)	1: H01-H09,N01,N02,N04,N05,N06,N08 2: N03,N07,N09
Final segment, Neglect/CVA, (2)	1: N03,N07,N09 2: S01-S10,N01,N02,N04,N05,N06,N08
Final segment, All ,(2)	1: H01-H09,N02,N05,N08,S01-S10 2: N01,N03,N04,N06,N07,N09

quite homogenous, and was assigned into a single cluster. The neglect patients, however, were assigned into two clusters. Reviewing their medical records revealed that all the patients in cluster #2 were diagnosed with only mild neglect.

When comparing pairs of populations, some interesting clusters have emerged. When healthy and CVA subjects were pooled together, all the healthy subjects were clustered together with two stroke patients who were closer to them than to the other stroke patients. This suggests that the border between healthy and stroke is not always clear cut. The healthy and neglect populations, produced three clusters, where the healthy were separate, and the neglect clustered again into two groups, severe and mild.

When pooling together the two patient populations, CVA and neglect, two of the mild neglect patients, N5 and N8, performed well enough to be "upgraded" to the CVA cluster. A similar trend was observed when we clustered all the subjects, as the severe neglect patients were in one cluster, some of the healthy were in another, and a middle cluster included all the CVA, the mild neglect and even two healthy subjects.

As before, we also focused at the initial and final segments of the motion. The initial segment essentially reproduced the pattern identified in the analysis of the entire movement. The clustering of the final segment produced a similar pattern, although not so distinct. For example, when clustering the CVA and healthy populations, one CVA patient (S3) and one healthy participant (H5) were joined together in one cluster, while everyone else were assigned to a separate cluster.

The key findings were reproduced also when employing k-means.

3.3.2 2D Experiment

Looking at Kohonen clustering for the 2D data (See Table 4), the only clustering that adhered to the medical condition was that of Healthy and CVA. The two populations clustered into four clusters. Aside from S10, who, as mentioned earlier, suffered no motor disability, the healthy participants occupied two separate clusters and so did the CVA patients. No explicit reason was found in their medical records, to account for this sub clustering. The rest of the clustering trials yielded no meaningful results.

Table 4: Clusters produced for 2D data.

Vector Size, Populations, (Num. of clusters allowed)	Kohonen Clusters
5 data points, Healthy/CVA, (7)	4: HA31-HA63,S10 5: HA4-HA10 6: S2,S3,S6,S8,S9 7: S1,S4,S5,S7
5 data points, Healthy Children/ TBI children, (7)	1: T9,HC12 2: T8,HC1-HC5,HC7,HC9, HC10,HC14-HC21 3: T2,T5,T6,T7,HC6,HC8,HC11,HC13 4: T1,T3,T4 7: HC3
5 data points, Healthy Children/ Healthy Adults, (7)	4: HA32,HA34,HA38,HA40,HA49, HA53,HC6,HC8,HC11 5: HA1-AH20,HA23,HA31, HA33,HA35,HA36,HA37,HA39, HA41-HA52,HC1,HC2,HC4,HC5, HC7,HC9,HC14,HC16-HC21 6:HA21,HA22,HC3,HC10,HC13,HC15 7: HC12
5 data points, TBI/CVA, (7)	1: S4,S8 3: S6 4: S1,S2,S9,T1,T3,T4,T7 5: S3,S7,T2,T5,T6,T8 6: S5,S10,T9
5 data points, All, (7)	3: S1,S2,S4-S9,T1-T4,T6,HC3 4: S3, T5,T7-T9,HC12,HC13 5: HA/HC 6: HA/HC,S10 7: HC8

4 DISCUSSION AND FUTURE DIRECTIONS

4.1 Discussion

In this study we demonstrated how machine learning tools may assist the clinician or scientist in analyzing data collected by VR platforms. This can be done even though these data are based on very small samples and even when the data is extremely noisy and partial. We proposed two approaches for achieving meaningful results.

First, two-class classification may assist in differential diagnosis. This was demonstrated as in both experiments, different patient population was diagnosed above average: CVA vs neglect and CVA vs, TBI, respectively. In this study, being a proof of concept, we picked medical conditions where we could assess the patients also in conventional methods. We believe that our approach will aid also in more hard to distinguish conditions.

Furthermore, from the scientific aspect, running such classifications can be done while using different segments of the data as input. The results may direct the researcher to the key components in motion or behavior which are sensitive to the classification. For example, the data here suggest that perhaps the difference in reaching behavior between neglect patients and non neglect CVA patients lies at the very beginning of the motion where the classification between them is quite high (89%). Such pointers may aid researchers in hypothesizing models of brain functions and in designing the experiments to validate them.

The zero-class approach suggested, especially in the 3D study, how the rigid distinction between various conditions may be misleading. It was shown how sometimes neglect patients behave in a similar way to non-neglect CVA patients or how certain CVA patients belong in the same cluster. This approach can point the rehabilitation professionals to better understanding and organization of heterogeneous or wide spectrum disorders.

4.2 Future Directions

One immediate goal is to apply one-class algorithms on these data. One-class filters are those that are trained and produced using only data from one-class, yet it produces a classification on new data that says the data point is in the class or not.

Building one class filters may assist the field of rehabilitation science in one of its severe shortcomings, which is the lack of large samples of clinical populations. One can only imagine the benefits of building one-class filters from different VR platforms and applications. We propose that upon finding relevant data segments we can accumulate data from different settings. After sufficient training of a set of one-class filters, one can bring a novel data vector and test it on these filters to see whether this patient tested positive for the "mild neglect" or "severe neglect" or "mild upper-left hemi-field but otherwise OK" etc. This may focus the clinicians in treating only the impaired faculties of the patients.

Preliminary results indicate that in our 3D data a one-class filter achieved 97% success rate in labeling "severe neglect". Thus this may be a promising direction.

Another direction would be to test our approach in current frontiers of neurological rehabilitation. One example would be finding a way to easily diagnose between spatial neglect and hemianopsia, which is related to different brain mechanisms, but leads to a behavior similar to that of neglect patients.

Similarly, it would be of significant value if zero-class clustering may aid in separating the wide spectrum of attention deficit disorders (ADD) into meaningful sub-categories.

Finally, in our vision for the long range, we see the possibility of "closing the loop" and using the classification and clustering methodology as keys for making rehabilitation protocols both adaptive and individualized. This is especially tempting in the context of rehabilitation in the virtual reality environment. What is needed is the development of a virtual model of the individual which we would want to extract automatically from data based on his performance in the VR sessions. Then an individual rehabilitative protocol can be obtained by simulating the behavior of an avatar in the VR; and simply testing how the avatar improves under a large variety of protocols. Once a good one is established, it can be immediately applied to the patient who is being treated in the same VR environment.

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