Using motor patterns for stroke detection

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Stroke is a leading cause of death and severe disability in the elderly, and poses a major challenge for public health. In recent years, there has been a rapid increase in the number of stroke victims in many countries, due to the aging population (*1, 2*). Moreover, stroke survivors are at a higher risk of suffering another stroke. Indeed, studies report that up to 40 percent of survivors suffer a new stroke within one year of a diagnosed stroke. Therefore, early detection of stroke in at-risk patients, including stroke survivors, is an important health challenge.

Previous studies have shown that the Trail Making Test (TMT) is an important means to detect stroke (*1*, *3*). However, conducting a traditional TMT requires the assistance of doctors, which is not always convenient. In this paper, we describe an accurate approach for automating stroke detection through a computer-based, body sensing game-based Trail Making Test (BSG-TMT), which in theory will allow for timelier intervention implementations. Our results demonstrate that the accuracy of a stroke diagnosis can be as high as 91 percent using only four selected motor pattern features (*4*). This accuracy can be significantly improved by including medical history features. These findings verify clinical observations and highlight the importance of using fine motor pattern features of the upper limbs and medical history features for detecting strokes.

Motor pattern feature selection

As shown in Figure 1, the proposed stroke detection framework consists of four steps: (1) data acquisition — collecting raw motion data using the proposed robust fingertip tracking method (*5*); (2) feature extraction — extracting the potential motor pattern features related to stroke from the raw motion data collected in Step 1 and identifying the patient's medical history features; (3) feature selection — applying a mutual information-based feature selection method to obtain the most representative features; and (4) classification — validating the discrimination ability of the selected features.

In Step 1 of the proposed detection framework, a Microsoft Kinect unit is used to collect raw depth sensor data while each subject is taking the BSG-TMT (*4*). The BSG-TMT is designed based on the widely accepted clinical TMT. The TMT requires the subject to connect a set of N dots, numbered 1, 2, …, N, in a strictly sequential order (starting with dot 1) as quickly as possible. In the BSG-TMT, the pen and paper used for traditional TMTs are replaced by the subject's fingertip and a computer screen, respectively. As illustrated in Figure 1, the fingertip is represented by the red bullet symbol and the numbered dots are represented by the numbered squares. If the subject is currently on dot N and makes a mistake by next connecting to a dot other than dot $N+1$, we say that a connection error has occurred. In this event, the subject has to retry until he connects to dot $N+1$. The test ends when the subject connects to dot N. Because it is difficult to identify patients who will suffer a stroke in the future, we collected data from stroke patients who had been recently discharged from the hospital and used the data to approximate the data for potential stroke patients. These selected patients are known to have a high likelihood of a new stroke occurrence, which provides us with a reasonable proxy for at-risk patients.

In Step 2, potential stroke-related motor pattern features are extracted from the data collected in Step 1. These features include the time the subject took to complete the BSG-TMT (A-Time); the test accuracy (T-Accuracy); the time the subject took to correct a connection error (C-Time); the mean (M-R-Length) and variance (V-Length) of the N–1 ratios of the fingertip movement path length to the straight-line distance between two consecutively numbered dots; the mean (M-Fingertip) time duration spent by fingertips at the dots; and the mean (M-R-Time) and variance (V-Time) of the ratios of the time needed to connect two consecutively numbered dots to the fingertip movement path length between the two dots. Medical history features, such as history of strokes, hypertension (HT), hyperglycemia (HG), coronary heart disease (CHD), and diabetes were also retrieved. In total, 13 features were studied.

To determine the most representative features for stroke detection, in Step 3 we adopted the mutual information-based feature selection method. This method automatically measures the importance of the 13 features, retaining the most representative features and discarding unnecessary ones. Initially, we used the finger motor pattern features to build the stroke detection model and tested the discrimination ability using 10-fold cross validation (*6*). We then ranked the combination of features in the order of testing accuracy. For each combination, we applied the 10-fold cross-validation again to get the final testing accuracy and selected the most discriminative combination as the final feature set. Similarly, we ranked the discrimination ability of the medical history features. We added the medical history features to the selected feature set one by one until no further classification performance improvements could be obtained.

In Step 4, the effectiveness of the selected features was validated through a recognition test on the subjects. We employed a single-hidden-layer neural network, b-COELM (*7*), which is very efficient and effective when the training set is small (*8*), to train a binary classifier to distinguish stroke patients from the control subjects based on the selected features.

Experimental analysis

We designed a study using human subjects to demonstrate the effectiveness of the proposed stroke detection method. Fifty stroke patients (16 women and 34 men, from ages 52 to 81) and 55 healthy elderly subjects (25 women and 30 men, from ages 30 to 68) were recruited for our experiments. Each subject was asked to take the BSG-TMT, and the entire session was automatically recorded by the system.

A feature selection experiment was then performed on the data. As shown in Figure 2, after seven iterations, the four most representative motor pattern features were selected, which improved the classification accuracy from 74 percent to 91 percent. After combining these features with the four selected medical features, the accuracy improved to nearly 100 percent (*4*). Table 1 shows the eight selected features. Our results indicate that motor pattern features are sufficient to detect stroke with reasonable accuracy, and the accuracy can be further improved by also considering the subjects' medical history. The experimental results have demonstrated for the first time that through combining motor pattern features and a patient's medical history features, a stroke can be accurately detected.

TABLE 1. Eight most discriminating features for stroke detection.

Category	No.	Feature name	Feature description
Motor pattern features	1	A-Time	Time the subject takes to complete the BSG-TMT
	2	M-Fingertip	Mean time that fingertips are on the dots
	3	C-Time	Time the subject takes to correct a connection error
	4	M-R-Time	The mean of the ratio for the time needed to connect two consecutively numbered dots to the path length taken between the two dots
Medical history features	5	HT	Whether the subject has hypertension
	6	HG	Whether the subject has hyperglycemia
	7	CHD	Whether the subject has coronary heart disease
	8	Stroke	Whether the subject has previously had a stroke

References

1. B. Wiberg, *Comprehensive Summaries of Uppsala Dissertations from the Faculty of Medicine* **540**, 65 (2010).
2. R. M. Reitan, *Percept.Motor Skills***8**, 271 (1958).
3. G. Prasad *et al.*,*J.Neuroeng.Rehabil.* **7**, 60 (2010).
4. H. C. Yu, X. D. Yang, Y. Q. Chen, J. F. Liu,*Proceedings of the 12th IEEE International Conference on Ubiquitous Intelligence and Computing* (UIC, Beijing, 2015), pp. 360-363.
5. H. C. Yu, Y.Q. Chen, J .F. Liu, G. B. Huang,*IEEE Intell. Syst.***28**, 55 (2013).
6. Wikipedia, https://en.wikipedia.org/wiki/Cross-validation_(statistics).
7. L. S. Hu *et al.*,*Pervasive Mob. Comput.***15**, 200 (2014).
8. K. Han, D. Yu, I. Tashev, *Proceedings of the 15th Annual Conference of the International Speech Communication Association (Interspeech 2014)* (ISCA, Singapore, 2014), pp. 223–227.

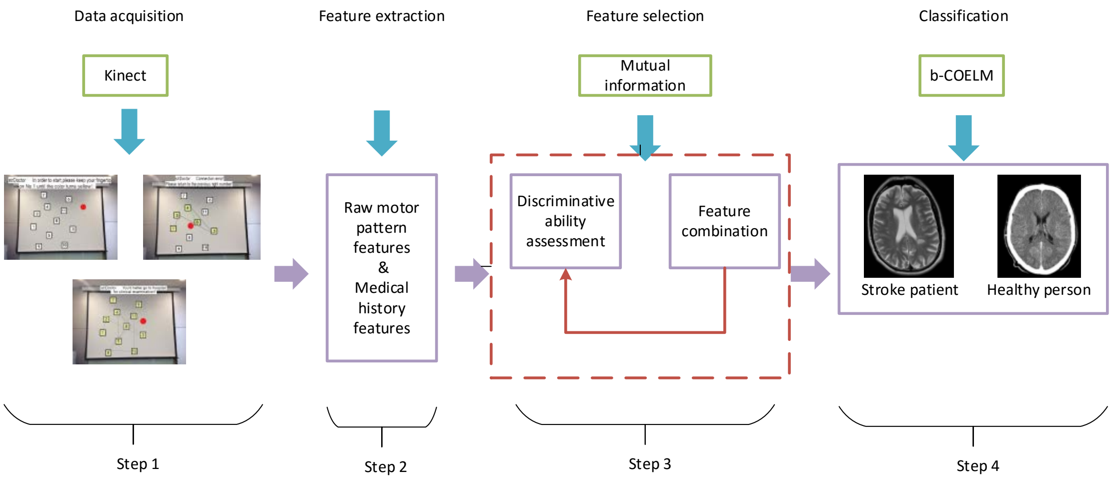

FIGURE 1.The proposed stroke detection framework.

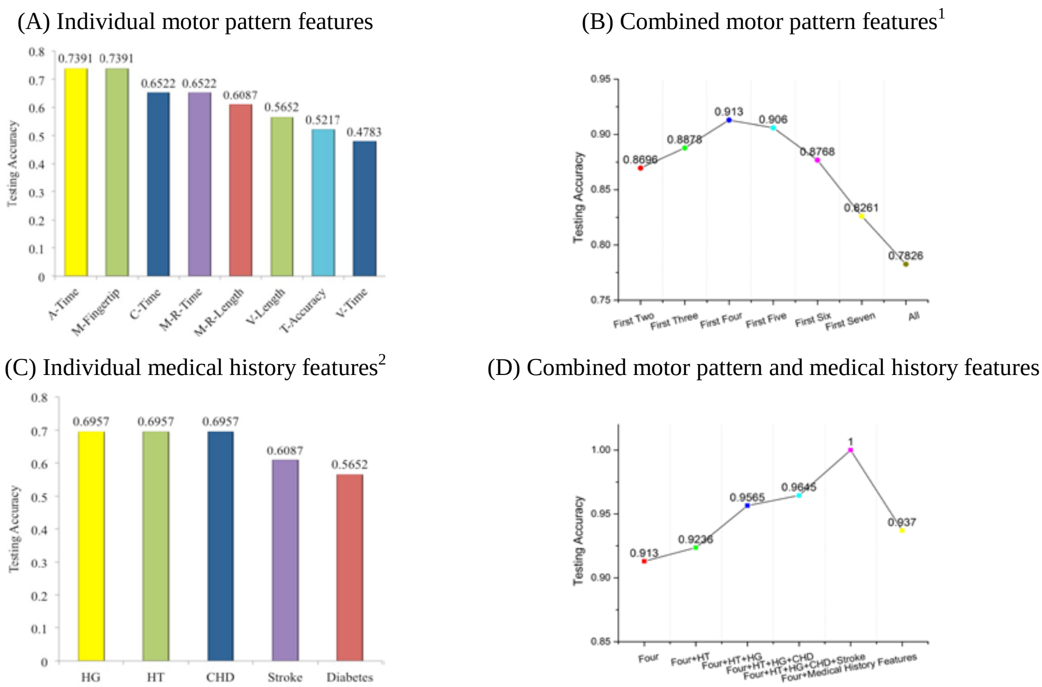

FIGURE 2. Results showing the accuracy of test data when selecting for representative features(*4*)
[1]First two/three/four… mean those corresponding features listed in graph (A).
[2]HG means hyperglycemia, HT means hypertension, and CHD means heart disease.

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