Off-Line and On-Line Vigilance Estimation Based on Linear Dynamical System and Manifold Learning

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***Abstract*— For many human machine interaction systems, to ensure work safety, the techniques for continuously estimating the vigilance of operators are highly desirable. Up to now, various methods based on electroencephalogram (EEG) are proposed to solve this problem. However, most of them are static methods and are based on supervised learning strategy. The main deficiencies of the existing methods are that the label information is hard to get and the time dependency of vigilance changes are ignored. In this paper, we introduce the dynamic characteristics of vigilance changes into vigilance estimation and propose a novel model based on linear dynamical system and manifold learning techniques to implement off-line and on-line vigilance estimation. In this model, both spatial information of EEG and temporal information of vigilance changes are used. The label information what we need is merely to know which EEG indices are important for vigilance estimation. Experimental results show that the mean off-line and on-line correlation coefficients between estimated vigilance level and local error rate in second-scale without being averaged are 0.89 and 0.83, respectively.**

I. INTRODUCTION

In the past few decades, studies have shown that vigilance estimation is very useful to our daily lives [1], [2] . Especially for many human machine interaction systems, to ensure work safety, the techniques for continuously estimating the vigilance of operators are highly desirable. Various signals are used for analyzing vigilance. Among them, electroencephalogram (EEG) has been proved very effective, and many important observations have been pointed out [3]. These include the positive correlation of vigilance and the P300 ERPs amplitude, the negative correlation of vigilance and theta rhythm activity, and the similarity between vigilance and the principal component of EEG spectrum. Based on EEG, various methods are proposed [4]–[6]. However, most of them are static supervised learning models. Task performance in a testing environment is usually used as the label information to tag the current vigilance stage. To overcome the fluctuations of EEG features, these static models adopt minute-scale average approach to smooth the EEG features, while the label information in some tasks is hard to get and sometimes not reliable. The on-line time delay for vigilance estimation is minute-scale.

Considering the factors mentioned above, we propose a novel dynamic model for vigilance estimation to improve our previous work [7], [8]. In this model, the accurate label information is not needed. What we need is merely to know which EEG indices are important for vigilance estimation. Then a dynamic model is designed by combining the spatial information of EEG and the temporal information of vigilance changes in second-scale. This is a data driven model. All of the parameters are estimated without label information. Our method has the following three main advantages over the existing approaches: a) What we need is merely to know which EEG indices are important for vigilance estimation, not including the accurate vigilance label information of EEG; b) Time series information of vigilance changes is adopted to improve the vigilance estimation accuracy; and c) Reliable second-scale vigilance estimation without any more time delay can be achieved.

This paper is organized as follows. In Section II, vigilance experimental setup is described. In Section III, the proposed models and data analysis process are presented. In Section IV, experimental results are described. Finally, some conclusions are given in Section V.

II. MATERIALS

A. Procedure and Subjects

This is a monotonous visual task. Subjects sit in a comfortable chair, two feet away from the LCD. There are four colors of traffic signs being presented in the LCD randomly by the NeuroScan $Stim^2$ software. There are more than 40 different traffic signs for each color. Each trial is 5.5∼7.5 seconds long, including 5∼7 seconds black screen and 500 millisecond traffic signs presented. The subjects are asked to recognize the sign color, and press the correct button on the response pad. There are 4 buttons on the response pad corresponding to the 4 different colors of traffic signs. A total of 7 healthy subjects of 19 to 28 years old have participated in this experiment. After training, each subject has finished at least one session, which is carried out in a small sound-proof room with normal illumination. Each session continues for more than one hour, during 13:00∼15:00 after lunch.

B. Data Collection

For each session, the visual stimulus sequence and response sequence are recorded by the NeuroScan $Scan$ software sampled at 500Hz. Meanwhile, a total of 62 EEG channels are recorded by the NeuroScan system sampled at

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500Hz synchronously, and filtered between 0.1 and 100Hz. The electrodes are arranged based on extended 10/20 system with a reference on the top of the scalp. Finally, 7 subjects have been recorded.

C. Vigilance Measurement

To evaluate the performance of our proposed model, a reference vigilance index is necessary. In our experiments, the local error rate of the subject's performance is used as the reference, which is defined as the current probability that the subject will fail to respond to a presented target within a time window with a constant width [9] [10]. Because the fluctuations of vigilance level with cycle lengths are usually longer than 4 minutes [9], the local error rate series are derived by computing the target false recognition rate within a 2-minute time window at 2-second step and the variance at cycle lengths shorter than 2 minutes is eliminated in our experiments.

III. Methods

A. EEG-Vigilance Model

Based on some assumptions, we give a definition of the EEG-vigilance model. If we take the EEG into two parts, vigilance-related EEG, E_v, and vigilance-unrelated EEG, E_o. Excluding the influence of vigilance-unrelated EEG, our assumptions can be described as follows:

- Continuous bijective map from vigilance stage to vigilance-relevant EEG, $M : V \mapsto E_v$, where V means vigilance level.
- Continuous mapping from EEG to EEG index, $F_i : E_v \mapsto X_i$, where X_i means EEG index, which is used to reflect vigilance level. There is no guarantee of bijection.
- For any different vigilance-relevant EEG, E_{v_i}, E_{v_j}, there at least exists one index, which can distinguish them: $\forall E_{v_i} \neq E_{v_j}, \exists F_k, s.t., F_k(E_{v_i}) \neq F_k(E_{v_j})$.
- For any EEG indices subset $\{X_i\}$, a corresponding index space, $S = (X_{S_1}, ..., X_{S_n})$ can be constructed. Then, according the above assumptions, we can find out an index space Y, and construct a continuous bijective mapping from EEG to the index space, $P : E \mapsto Y$, where $P(E_v) = (F_{Y_1}(E_v), ..., F_{Y_m}(E_v)) = (X_{Y_1}, ..., X_{Y_m}) = Y$.

Then, it is easy to prove that there exists an index space, Y, and a continuous bijective mapping from vigilance to this index space, G: $V \mapsto Y$, where, $G(V) = (G_1(V), ..., G_m(V)) = (F_1(M(V)), ..., F_m(M(V)) = P(M(V)) = Y$. And, this mapping is just the EEG-vigilance model,

$$Y = \{X_{Y_1}, ..., X_{Y_m}\} = (G_1(v), ..., G_m(v)) = G(v). \quad (1)$$

This EEG-vigilance model is based on no vigilance-unrelated EEG assumption. However, in practice, the influence of E_o is very large. For this EEG-vigilance model, after considering E_o, the EEG index, $F_i(E_v)$ has been changed to $X_i = F_i(E_v + E_o)$, and the mapping G is no longer satisfied. The differences between $F_i(E_v)$ and $F_i(E_v + E_o)$ can be shown by Taylor expansion as follows,

$$\begin{aligned} F_i(E_v + E_o) = F_i(E_v) + DF_i(E_v)E_o + \\ \frac{1}{2}{E_o}^t D^2 F_i(E_v) E_o + ..., \end{aligned} \quad (2)$$

where DF_i and D^2F_i are the first order and second order derivatives of F_i. From Eq. 2, we can see that E_o and $\{F_i\}$ are the key disturbing factors of EEG index. To minimize the effect of E_o, we can choose the most vigilance-related brain regions to measure EEG, or use some spatial filter techniques to filter them. To minimize the effect of $\{F_i\}$, we can design some EEG indices functions, compared to $F_i(E_v)$, which have relatively smaller first order and high order derivatives of E_v. The ultimate goal is to get an approximate $F_i(E_v)$ from $F_i(E_v + E_o)$, and make Eq. 1 approximately satisfied.

In general, vigilance is considered as a continuous one-dimensional psychophysiological variable [10]. Then, from Eq. 1, vigilance can be seen as a one-dimensional manifold embedded in a high-dimensional EEG index space. Since G is a continuous bijective mapping, vigilance is the only embedded manifold in the EEG index space. By using nonlinear dimensionality reduction method, the vigilance can be directly found out from the EEG index space without any label information.

B. Dynamic Model For Vigilance Estimation

The vigilance-unrelated EEG influence minimization methods above are all based on static method. Without being averaged, the EEG indices generated by them are not good enough to support second-scale vigilance information clearly.

Here, we propose a dynamic model, by making use of the time dependency of vigilance changes, to further reduce the influence of vigilance-unrelated EEG, and to find out the vigilance trajectory from the EEG index space without using any label information.

The first part of this model is to filter the EEG index, which is based on linear dynamical system. After being preprocessed by static methods, there still exist differences between $F_i(E_{v_t})$ and $F_i(E_{v_t} + E_{o_t})$. If the differences are considered as a gaussian noise, we can get

$$F_i(E_{v_t} + E_{o_t}) = F_i(E_{v_t}) + w_t, \quad (3)$$

where w_t is the gaussian noise with mean $\bar{w}$ and variance Q. As mentioned before, the vigilance changes are time dependent. If the dependence is considered as Gaussian, we can get

$$F_i(E_{v_t}) = AF_i(E_{v_{t-1}}) + v_t, \quad (4)$$

where A is a transition matrix and v_t is a gaussian noise with mean $\bar{v}$ and variance R. Combining Eq. 3 and Eq. 4, we can form a linear dynamical system (LDS) as follows,

$$\begin{aligned} x_t &= z_t + w_t, \\ z_t &= Az_{t-1} + v_t, \end{aligned} \quad (5)$$

where x_t denotes $F_i(E_{v_t} + E_{o_t})$, z_t denotes $F_i(E_{v_t})$, and only x_t is known. This equation can also be expressed in an equivalent form in terms of Gaussian conditional distributions,

$$\begin{aligned} p(x_t|z_t) &= \mathcal{N}(x_t|z_t + \bar{w}, Q), \\ p(z_t|z_{t-1}) &= \mathcal{N}(z_t|Az_{t-1} + \bar{v}, R). \end{aligned} \tag{6}$$

The initial state is assumed to be,

$$p(z_1) = \mathcal{N}(z_1|\pi_0, S_0). \tag{7}$$

The above model is parameterized by $\theta = \{A, Q, R, \bar{w}, \bar{v}, \pi_0, S_0\}$. Just based on the observation sequence $\{x_t\}$, θ can be directly determined using maximum likelihood through the EM algorithm [11]. To inference the latent states $\{z_t\}$ from the observation sequence $\{x_t\}$, the marginal distribution, $p(z_t|X)$ must be calculated. Then the latent state can be expressed as,

$$z_t = E(z_t|X), \tag{8}$$

where E means expectation. This marginal distribution can be achieved by using messages propagation methods [11]. For on-line inference, X is set as $\{x_1, ..., x_t\}$, while for off-line inference, X is set as $\{x_1, ..., x_n\}$, including the data observed after x_t.

The second part of this model is to reconstruct the vigilance trajectory from the filtered EEG index space. Since vigilance is the only embedded manifold. The vigilance trajectory can be directly estimated by manifold learning method. However, the nonlinear manifold learning methods usually can not be used on on-line condition. To solve this problem, we extend the landmark-isomap to an on-line algorithm [12]. Isomap is a manifold learning algorithm, which extends multidimensional scaling (MDS) by incorporating the geodesic distance. And landmark-isomap is the accelerating algorithm for Isomap. This on-line algorithm can be achieved by two step: First, on off-line condition, we use the landmark-isomap algorithm to calculate the geodesic distance D and the embedding coordinates, L, of the random selected landmark points,

$$L = \begin{pmatrix} \sqrt{\lambda_1} \cdot v_1^T \\ \vdots \\ \sqrt{\lambda_m} \cdot v_m^T \end{pmatrix}, \tag{9}$$

where λ_i and v_i are the ith largest eigenvalues and the corresponding eigenvectors calculated by MDS in landmark-isomap, and m is the dimension number of the embedded manifold. Second, on on-line condition, for a new sample z, we assume this sample obeys the same distribution as the landmarks points. Then we can use the Euclidean distance between the new sample and its k nearest landmark points, combined with D, to calculate the geodesic distance, d, between the new sample and the landmark points. If the landmarks points' distribution are dense enough, the on-line calculated geodesic distance is much close to the off-line calculated geodesic distance. Then the embedding coordinate of the new sample can be calculated by

$$l = \frac{1}{2} L^{\#}(\bar{\Delta} - \Delta), \tag{10}$$

where $\bar{\Delta}$ is the column mean of squared distance matrix S ($S_{ij} = D_{ij}^2$), Δ ($\Delta_i = d_i^2$) is the column vector of squared distances between new sample and landmark points, and $L^{\#}$ is the pseudoinverse transpose of L,

$$L^{\#} = \begin{pmatrix} v_1^T / \sqrt{\lambda_1} \\ \vdots \\ v_m^T / \sqrt{\lambda_m} \end{pmatrix}. \tag{11}$$

C. Data Analysis

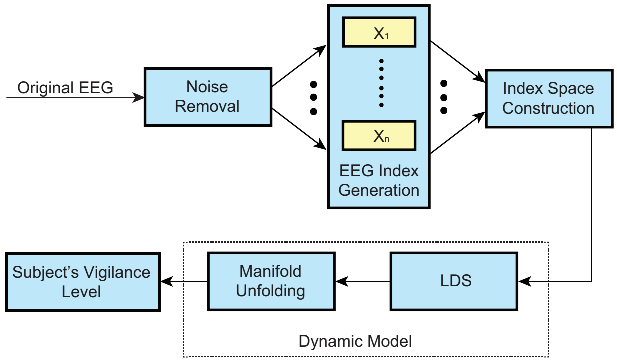

Fig. 1. Flowchart of data analysis for vigilance estimation.

20 EEG channels are used for vigilance estimation, which are measured from the posterior regions of the scalp. The flowchart of data analysis is depicted in Fig. 1.First, a band-pass filter (1Hz-50Hz) is used to remove the low-frequency noise and the high frequency noise. Then the power spectral density (PSD) of EEG is calculated by every 2 seconds, and the principal components of the PSD are calculated as the EEG index. Next, select the EEG indices which have fewer differences between $F_i(E_v + E_o)$ and $F_i(E_v)$, to construct the index space. Finally, the selected EEG indices are sent to the dynamic model, and the subject's vigilance level is estimated. In our experiment, the EEG indices are generated from the principal components of the PSD, and the top three most vigilance-related components from the first 10 principal components of the PSD, according to the reference vigilance index, are selected out for index space construction. However, in practice, the EEG indices can be generated by other EEG features, and selected by prior knowledge.

IV. Results and Discussions

To evaluate the performance of the dynamic model (DM), the local error rate of task performance is used as reference vigilance index. Besides, for performance comparison, the other three kinds of methods, M1, M2, M3, are designed and used for vigilance estimation. Each method consists of two parts, EEG index filter, and vigilance trajectory detection. The EEG index filter candidates are LDS-based filter used for DM and M1, and moving-averaged filter within 2 minutes used for M2 and M3. The vigilance trajectory detection methods candidates are manifold learning used for DM and M2, and EEG indices linear summation used for M1 and M3. The correlation coefficient between the estimated vigilance level and the reference vigilance index is calculated to evaluate the model's performance. Usually, long period of repeated operations can easily cause dysphoric mood, which will affect the subject's performance. In order to reduce these vigilance-unrelated disturbances of task performance, only the first 40 minutes EEG and task performance of each session are used for performance evaluation.

A. Results

After being properly scaled, the estimated vigilance level by dynamic model and the reference vigilance index are shown in Fig. 2. The performance comparison results between different methods are shown in Table I. For on-line condition, without time delay, only DM and M1 combined with on-line LDS-based filter are feasible, therefore, only their performance comparison results are shown in the on-line part of Table I.

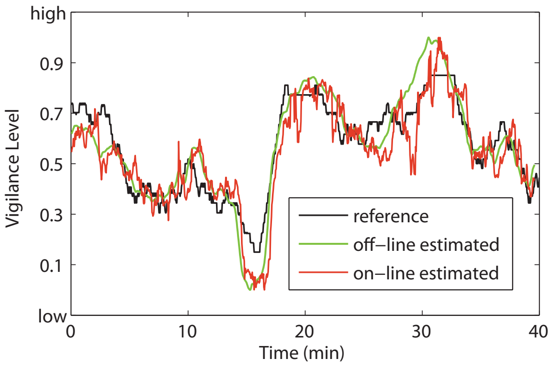

Fig. 2. Estimated vigilance level by dynamic model from session 2 against the reference vigilance index. The off-line and on-line correlation coefficients between them are 0.92 and 0.82, respectively.

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT METHODS

Session	**Off-line**				**On-line**	
	DM	M1	M2	M3	DM	M1
S1	0.93	0.83	0.75	0.67	0.86	0.79
S2	0.92	0.82	0.75	0.78	0.82	0.74
S3	0.88	0.87	0.86	0.87	0.81	0.79
S4	0.82	0.81	0.81	0.80	0.78	0.75
S5	0.85	0.78	0.81	0.87	0.80	0.76
S6	0.88	0.86	0.85	0.85	0.83	0.82
S7	0.93	0.92	0.92	0.92	0.93	0.90
Average	0.89	0.84	0.82	0.81	0.83	0.79

B. Discussions

As shown above, the following conclusions can be drawn. 1) LDS-based filter is better than moving-averaged filter. Because DM performs better than M2, and M1 performs better than M3. And whether using LDS-based filter is the only different between each pair of methods. 2) Manifold learning is better than linear summation, especially combined with LDS-based filter. Because DM performs better than M1, and M2 performs better than M3. At this time, whether using manifold learning is the only difference between each pair of methods. However, M2's performance is close to M3's. This is mainly caused by information lost derived from moving-averaged. 3) The off-line methods perform better than the on-line methods, because they can use lots of information after the current time. But, for real-time vigilance estimation, only on-line methods are feasible. 4) Both for off-line and on-line conditions, DM's performance is the best, and the estimated results match well with the reference vigilance index. Therefore, vigilance is just the manifold embedded in EEG indices space.

V. CONCLUSIONS

In this paper, an EEG-based dynamic model is proposed, which assumes vigilance as a manifold embedded in the EEG index space. The parameters of this dynamic model can be determined directly from the EEG data without using any label information. The label information used in this model is merely to know which EEG indices are important for vigilance estimation. In practice, these information can be achieved by prior knowledge. Compared with the existing methods, this dynamic model can achieve a reliable and high accurate second-scale vigilance changes estimation without time delay for both off-line and on-line conditions, and the manifold assumption of vigilance is also verified in our experiments. In the future, nonlinear dynamical model will be explored for vigilance analysis.

REFERENCES

[1] R. Molloy, and R. Parasuraman, "Monitoring an automated system for a single failure: vigilance and task complexity effects", *Human Factors*, vol. 38, pp. 311-322, 1996.

[2] M.B. Weinger, "Vigilance, Boredom, and Sleepiness", *Journal of Clinical Monitoring and Computing*, vol. 15, pp. 549-552, 1999.

[3] B.S. Oken, M.C. Salinsky, and S.M. Elsas, "Vigilance, alertness, or sustained attention: physiological basis and measurement", *Clinical Neurophysiology*, vol. 117, pp. 1885-1901, 2006.

[4] T.P.Jung, S. Makeig, M. Stensmo, and T.J. Sejnowski, "Estimating Alertness from the EEG Power Spectrum", *IEEE Transactions on Biomedical Engineering*, vol. 44, pp. 60-69, 1997.

[5] A. Vuckovic, V. Radivojevic, A.C.N. Chen, and D. Popovic, "Automatic recognition of alertness and drowsiness from EEG by an artificial neural network", *Medical Engineering & Physics*, vol. 24, pp. 349-360, 2002.

[6] C.T. Lin, R.C. Wu, S.F. Liang, W.H. Chao, T.J. Chen, and T.P. Jung, "EEG-Based Drowsiness Estimation for Safety Driving Using Independent Component Analysis", *IEEE Transactions on Circuits and Systems*, vol. 52, pp. 2726-2738, 2005.

[7] L.C. Shi, H. Yu, and B.L. Lu, "Semi-Supervised Clustering for Vigilance Analysis Based on EEG", *Proceedinds of International Joint Conference on Neural Networks*, Orlando, US, pp. 1518-1523, 2007.

[8] L.C. Shi, and B.L. Lu, "Dynamic Clustering for Vigilance Analysis Based on EEG", *Proceedings of International Conference of the IEEE Engineering in Medicine and Biology Society*, Vancouver, BC Canada, pp. 54-57, 2008.

[9] S. Makeig and M. Inlow, "Lapse in alertness: coherence of fluctuations in performance and EEG spectrum", *Electroencephalography and Clinical Neurophysiology* , vol. 86, pp. 23-35, 1993.

[10] S. Makeig and T.P. Jung, "Changes in alertness are a principal component of variance in the EEG spectrum", *NeuroReport*, vol. 7, pp. 213-216, 1995.

[11] R.H. Shumway and D.S. Stoffer, *Time Series Analysis and Its Applications: With R Examples*, Springer, 2nd edition, 2006.

[12] V. de Silva and J.B. Tenenbaum, "Global versus Local Methods in Nonlinear Dimensionality Reduction", *Advances in Neural Information Processing Systems*, vol. 15, pp. 705-712, 2003.