Estimation of Driver's Fatigue Based on Steering Wheel Angle

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Abstract. Driver's fatigue has been verified as a major factor in many traffic accidents. The estimation of driver's vigilance by steering wheel angle is good way because it is a non-invasive method compared with EEG. An adaptive vigilance estimation methodology based on steering wheel angle information is proposed. The sample data classification index is built from EEG and PVT information of ten driver's virtual driving experiment on driving simulator. According to the geometry information of road centerline and the location of the automobile center, a new algorithm is proposed to compute the lane deviation. The correlation coefficient between steering wheel angle and lane deviation are computed, and the results show that their correlation level is 0.05. Based on the steering wheel angle, the driver fatigue evaluation model is established by the Bayesian Network (BN). The structure and parameters for BN model are determined after adaptive training. The experiment results verified that this model is effective to identify driver's fatigue level.

Keywords: Driver fatigue; Steering wheel angle; Lane deviation; Bayesian Network model.

1 Introduction

Driver fatigue is a major factor attribute to traffic accident, and the statistics show that traffic accidents caused by driver drowsy accounts for about 20% of the total number of accidents, and more than 40% of serious traffic accident [1]. It has great safety significance to detect driver fatigue level quickly and efficiently.

Many research results have been achieved in detecting driver fatigue, such as physiological signal [2-4], driver's face expression [5-9] and so on. However, these methods have obvious shortcomings: the acquisition of physiological signal requires putting sensor on the driver's body which increases the cost and makes the driver uncomfortable especially in long-time driving; The detection of driver facial expression is influenced by the illumination, especially when the driver wear glasses; Also the information of eyelid movement (Perclos[5]) is hard to obtain in the high bright condition.

At present, driver's manipulation signal attracts more attention in the field of driver fatigue detection. Skipper, etc. [10] found the maximum and MSE (Mean Square Error) of lane deviation in drowsy state is larger than alert state. Siegmund et al [11] constructed three weight functions based on steering wheel angle in time domain,

D. Harris (Ed.): Engin. Psychol. and Cog. Ergonomics, HCII 2011, LNAI 6781, pp. 145–155, 2011.

frequency domain and amplitude domain respectively, and then established the index function called SED (Subjective Evaluation of Drowsiness) to evaluate the fatigue level. The experiment results show that SED is larger in drowsy state. Based on the analysis of steering wheel angle in time domain, Eskandarian et al [12] found that if the steering wheel angle is changed large firstly, and then changed little in a certain period time which means the driver is mostly in drowsy state.

From the results of above research, the lane deviation and steering wheel angle can be used to evaluate the driver fatigue level. The advantages of these methods are that it is little affected by the illumination and convenient for the driver because of its non-intrusive detection. However, the accuracy of these non-intrusive methods is lower. In order to improve its accuracy, the Bayesian Network (BN) method is used to build the fatigue level evaluation model in this paper.

The structure of this paper is organized as follows: firstly, the data acquisition process is introduced; secondly, a general algorithm is present to compute the lane deviation and eliminate the road curvature; then, the methods to separate the sample data into alert and drowsy state are provided; after that, the model to evaluate the driver fatigue level is established with the help of the BN method.

2 Method

2.1 Apparatus

A self-developed driving simulator (Fig.1) was used to detect driver fatigue. The hardware of driving simulator includes the Logitech steering wheel called MOMO force feedback racing wheel, Logitech camera and so on. The software of driving simulator is composed of the scene rendering system, the audio rendering system, the automobile dynamics model and the video capture system and so on. The Logitech camera is installed on the dashboard to collect driver's facial expression during driving. The driver's EEG signal is collected by NicoletOne Ambulatory EEG (Fig.2).

Fig. 1. The driving simulator and virtual driving scene

Fig. 2. NicoletOne Ambulatory EEG

2.2 Subjects

Ten healthy male drivers ranging from 22 to 35 old (Age: 28.1±3.6) were enrolled in this experiment. They all had a legal driver license and normal sleep-wake habits. Also they must have good sleep quality and no physical barrier before the experiment.

2.3 Experiment Arrangement

The experiment is divided into three periods: dawn (00:30-06:00), morning (8:00-11:30), noon (12:30-15:30). Drivers are instructed to drive at 80 km/h for straight line section and 40km/h for curve section. The virtual driving scene is monotonous that make the driver tend to become drowsy. The road is 100 km long composed of 4 lanes with 3.5 meters wide. Drivers are required to complete all the tasks and make proper manipulation to ensure safe driving. Before the experiment, all the drivers have a chance to be familiar with the experiment procedure.

3 Data Analysis

3.1 Lane Deviation

In this virtual driving scene, there are two kinds of road centerlines (curve and straight line), so the lane deviation is computed separately. Fig.3 shows a part of road centerline. AB, CD, EF, GH is the straight line sections, and BC, DE, FG belong to the curve sections.

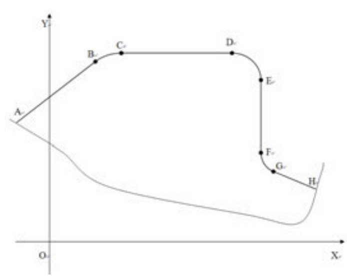
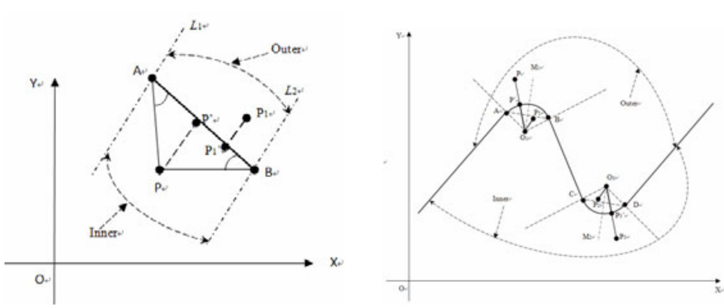


Fig. 3. A part of road centerline in driving scene



(a) straight line (b) curve section

Fig. 4. The identified algorithm

Fig.4 (a) shows the identified algorithm for straight line. A, B is the two endpoints of one straight line section. L_1, L_2 is the boundary line of AB section. If the point P, P_1 located between line L_1 and line L_2, the point belongs to AB section. Taking the point P for example, the angle of PAB and PBA are no more than 90 degree, so the cosine of PAB and PBA are no less than zeros.

$$\text{As}\begin{cases} \overrightarrow{PA}\bullet\times\overrightarrow{BA} = \left|PA\right|\bullet\left|BA\right|\bullet\cos(PAB) \\ \overrightarrow{PB}\bullet\times\overrightarrow{AB} = \left|PB\right|\bullet\left|AB\right|\bullet\cos(PBA) \end{cases} \tag{1}$$

$$\text{Then } S_{straight} = (\overrightarrow{PA}\bullet\times\overrightarrow{BA})\times(\overrightarrow{PB}\bullet\times\overrightarrow{AB}) \geq 0$$

If $S_{straight}$ is no less than zero, the point P belongs to the AB section; otherwise it doesn't belong to AB.

Fig.4 (b) shows the identified algorithm for curve line. O_1 is the center of arc AB. A, B is the endpoints of arc; P is the automobile position. O_1M_1 is the perpendicular bisector of AO_1B. AO_1, BO_1 is the boundary line. If the point located between these two lines, it belongs to AB curve section. Take the point P for example, it can be seen from Fig.4 (b) that the angle of PO_1M_1 is no larger than AO_1M_1, so the cosine of PO_1M_1 is no smaller than that of AO_1M_1.

$$\begin{gathered} \begin{cases} \overrightarrow{M_1O_1}\bullet\times\overrightarrow{PO_1} = \left|M_1O_1\right|\bullet\left|PO_1\right|\bullet\cos(M_1O_1P) \\ \overrightarrow{M_1O_1}\bullet\times\overrightarrow{AO_1} = \left|M_1O_1\right|\bullet\left|AO_1\right|\bullet\cos(M_1O_1A) \end{cases} \Rightarrow \\ S_{curve} = \overrightarrow{M_1O_1}\bullet\times\overrightarrow{PO_1} - \overrightarrow{M_1O_1}\bullet\times\overrightarrow{AO_1}\times\frac{\left|PO_1\right|}{\left|AO_1\right|} \geq 0 \end{gathered} \tag{2}$$

If the value of S_{curve} is no less than zero, the point belongs to current AB curve section.

Considering the two kinds of road centerline, the lane deviation can be computed as Eq. (3).

$$\begin{gathered} D_L = \frac{x(y_2 - y_1) + y(x_1 - x_2) - x_1y_2 + x_2y_1}{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}} \quad \text{straight\_line} \\ D_C = \sqrt{(x_a - x_0)^2 + (y_a - y_0)^2} - \sqrt{(x - x_0)^2 + (y - y_0)^2} \quad \text{curve} \end{gathered} \tag{3}$$

Where: D_L *and* D_C is the lane deviation in the straight line section and curve section respectively; x_1, y_1, x_2, y_2 is the coordinate value of two endpoints in the straight section; x, y is the current coordinate location value of automobile center; x_0, y_0 is the coordinate value of curve center; x_a, y_a is the coordinate value of one endpoints of curve.

In the virtual driving scene, all the road centerlines is constructed to form a closed loop, so the point can be located in the inner or outer of the closed loop. For the straight line section in Fig.4 (a), P is the inner point and P_1 is the outer point, so the lane deviation of P is positive and P_1 is negative. For the curve section in Fig.4 (b), P and P_2 are in the outer section, P_1 and P_3 are in the inner section. However the lane deviation for P /P_3 is positive and P_1/P_2 is negative which is different with straight line. In order to ensure the sign of the lane deviation can be acted as the judgment parameter to distinguish the inner section and outer section, C_{sign} is introduced to ensure the sign of lane deviation for P/P_2 be negative and P_1/P_3 be positive (Eq.(4)).

$$C_{sign} = x_{O_1}(y_B - y_A) + y_{O_1}(x_A - x_B) - x_A y_B + x_B y_A \tag{4}$$

So the lane deviation can be computed as Eq. (5)

$$\begin{aligned} D_L &= \frac{x(y_2 - y_1) + y(x_1 - x_2) - x_1 y_2 + x_2 y_1}{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}} \quad \text{straight\_line} \\ D_C &= (\sqrt{(x_a - x_0)^2 + (y_a - y_0)^2} - \sqrt{(x - x_0)^2 + (y - y_0)^2}) \times C_{sign} \quad \text{curve} \end{aligned} \tag{5}$$

3.2 The Road Curvature Elimination

In the straight line section, the steering wheel angle only reflects the driver's steering adjustments, which would be affected by the road curvature in the curve section. It must be eliminated in the curve section to ensure the steering wheel angle only reflect the steering adjustments.

The curve section is divided into three parts: the enter part, the middle part and the exit part. The data of steering wheel angles are divided into groups (5 data for one group). The algorithm of road curvature elimination is described as follows:

1. *The enter part*

When the automobile is from straight line section to curve section, the steering wheel angle is from small to large until it waves around a special value. The identification of this procedure is as follow:

$$\begin{cases} std(A_{s,i}) > A_t \\ std(A_{s,i+1}) < A_t \end{cases} \quad i = 1, 2, \cdots, r \tag{6}$$

Where: std is the function to compute the standard error of data; A_t is the provided angle which used to distinguish the steering wheel angle belongs to the transition part (the enter or exit part of curve section) or not.

Then the steering wheel angles in the group between *first* and r^{th} belong to the enter part of curve section. The curvature in this part can be eliminated as Eq. (7)

$$A_{s,i,j} = \frac{(A_{s,i,j} - \frac{1}{5}\sum_{j=1}^{5} A_{s,i,j})}{\frac{1}{5}\sum_{j=1}^{5} A_{s,i,j}} \quad i = 1, 2, \cdots, r \tag{7}$$

2. *The middle part*

While the automobile is located in the middle part of curve section, the steering wheel angle changes at a small range. The identification algorithm of this part is as follow:

$$\begin{cases} std(A_{s,i}) < A_t \\ std(A_{s,i+1}) > A_t \end{cases} \quad i = r+1, r+2, \cdots, s \tag{8}$$

It can be seen from above that the driving steering wheel angle between (r+1)th and sth group belong to the middle part of curve section.

The curve curvature in this part can be eliminated by the method as Eq. (9).

$$A_{s,i,j} = A_{s,i,j} - \frac{1}{5}\sum_{j=1}^{5} A_{s,i,j} \quad i = r+1, r+2, \cdots, s \tag{9}$$

3. The exit part

While the automobile is driving from curve to straight line section, the steering wheel angle is from large to small until it waves around a special value. The curvature elimination in these groups can be eliminated as Eq. (10).

$$A_{s,i,j} = \frac{(A_{s,i,j} - \frac{1}{5}\sum_{j=1}^{5} A_{s,i,j})}{\frac{1}{5}\sum_{j=1}^{5} A_{s,i,j}} \quad i = s+1, s+2, \cdots, n \tag{10}$$

Fig. 5 shows the steering wheel angle before and after the road curvature. It can be seen that the steering wheel angle after curvature elimination only reflects the steering adjustments.

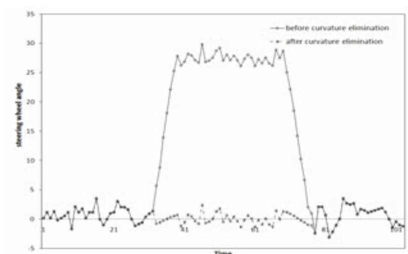


Fig. 5. The road curvature elimination

3.3 The Sample Data Classification

In this study, the sample data is classified into two fatigue level (alert & drowsy) with reference to the EEG, PVT and driving video.

EEG. As the EEG signal is regarded as the gold index to evaluate the driver fatigue level, it is introduced to be an index to classify the sample data. The driver's EEG signal is collected by NicoletOne Ambulatory with the sampling frequency of 200 Hz. The EEG signals are transformed to frequency domain by FFT method. It can be separated into 4 wave bands: δ (0.3-3.5 Hz),

θ(4-8Hz), α(8-13Hz), β(14-20Hz). A significant increase of θ and α activity, and a slight decrease of β activity has been indicate the drowsy state. [2,13]. Based on this results, the power spectrum ratio of θ and α relate to β called $R_{(\theta+\alpha)/\beta}$ is considered as the index to evaluate the driver fatigue level.

$$R_{(\theta+\alpha)/\beta} = \frac{A_\theta + A_\beta}{A_\beta} \tag{11}$$

Where: $A_\theta, A_\alpha, A_\beta$ is the power spectrum of θ, α and β respectively.

The EEG signal is grouped according to a given time interval (240 seconds). Then the mean power spectrum of each band is computed. The index for detect driver fatigue is computed as Eq. (12).

$$\begin{aligned} R_{eeg} = \min(\frac{1}{A_{eeg}}(\lambda_1\rho_1 \times mean(\frac{A_{\theta,i}+A_{\alpha,i}}{A_{\beta,i}})+ \\ \lambda_2\rho_2 \times std(\frac{A_{\theta,i}+A_{\alpha,i}}{A_{\beta,i}})),1) \quad i=1,2,\cdots,n \end{aligned} \tag{12}$$

Where: min is the function to compute the minimum value ; mean is the function to compute the mean value; std is the function to compute the MSE; A_{eeg} is the normalized results of $R_{(\theta+\alpha)/\beta}$; ρ_1, ρ_2 is the factor with reference to the individual differences; λ_1, λ_2 is the weight coefficient.

PVT. PVT test is proved to be an efficient method to evaluate the driver fatigue level. The score of driver's PVT test is composed of two parts: the response time and the accuracy of judgment. The score of PVT test for driver fatigue level is calculated by Eq. (13).

$$R_{PVT} = \min(w \bullet (w_1 \bullet \frac{t_R}{t_{SR}} + w_2 \bullet a_{PVT}),1) \tag{13}$$

Where: R_{PVT} is the score of PVT test for driver fatigue level; t_R is the response time; tSR is the mean response time when the driver in alert state; aPVT is the accuracy of judgment; w is a weight coefficient to indicate individual differences; w1, w2 is the weight coefficient.

Besides the EEG signal and PVT test, the driving video is as an additional index to evaluate the fatigue level. The score of driving video for fatigue level can be computed refer to the Perclos [5]. The final index of driver fatigue level is calculated by Eq. (14).

$$R_f = \rho_p \times R_{pvt} + \rho_e \times R_{eeg} + \rho_v \times R_v \tag{14}$$

Where: R_f is the final scores of driver fatigue level; R_V is the score of video assessment; ρ_p, ρ_e, ρ_v is the weight coefficient. In this paper, ρ_p=0.5, ρe=0.35, ρv=0.15.

3.4 The Correlation of Steering Wheel Angle and Lane Deviation

The lane deviation and steering wheel angle collected in driving experiment are classified into alert and fatigue level. The correlation coefficient between lane deviation and steering wheel angle is computed under these two fatigue levels. These two types of data are processed to eliminate the noise and road curvature before the computation. Tab.1 shows that the steering wheel angle has high correlation with lane deviation. As the steering wheel angel is collected easily, it is chose to be the index to evaluate the driver fatigue level in this paper.

Table 1. The correlation coefficient

Fatigue level	alert	drowsy
Correlation Coefficient	0.3568	0.3198

4 Results

4.1 Data Processing

In order to meet the demand of BN model and reflect the distribution of steering wheel angle in a certain time interval, the steering wheel angle is discrete and normalized.

Discretization. The steering wheel angle is discrete by Eq. (15), Eq. (16).

$$\text{Initialization}: Q_{a,i} = 0, \quad i = 1, \cdots, n \tag{15}$$

$$Q_{a,e} = 1, \quad e = \max(\min(floor(\frac{a - a_m}{L_a}) + \frac{n}{2} + 1, n), 1) \tag{16}$$

Where: Q_a is the vector after the data is discrete; a is the steering wheel angle; a_m is the mean steering wheel angle; floor is a function to choose the integer round towards minus infinity; L_a is the length of every interval. Choosing different value for L_a, Q_a can be calibrated for different driving behavior. Large values of L_a are used for driver with large steering wheel adjustment behavior while they are drowsy.

Normalization. After the data being discrete, all data in one time interval should be summed up, and then the data have to be normalized by Eq. (17).

$$Q_{a,i} = \frac{\sum_{j=1}^{20} Q_{a,ij}}{\max(\sum_{j=1}^{20} Q_{a,ij})}, \quad i = 1, \cdots, n \tag{17}$$

Where : $Q_{a,i}$ is the normalized result of steering wheel angle in the i^{th} time interval.

4.2 BN Model

BN model is a probabilistic graphical model that represents a set of random variables and their conditional dependences via a directed acyclic graph (DAG). BN has several advantages for data analysis: handle situation where some data are missing; gain understanding about a problem domain and predict the consequences of intervention; provide an ideal representation for combining prior knowledge and data; offer an efficient and principled way for avoiding the over fitting of data [14].

It can be seen from Fig.6 that the steering wheel angle is almost the normal distribution. Considering steering wheel angle being the normal distribution, a new BN model is proposed to detect driver fatigue level based upon Gaussian mixture models (GMM) which was usually used as classification tool [16].

The model is a two-class, two component mixture model: class 1 for alert state and class 2 for drowsy state. Its structure is described in Fig.7.

In this paper, the output (Node 3, the dimensional feature) and the class (Node 1, alert and drowsy) are observed. The type of Conditional probability Distribution (CPD) of driver fatigue level and the steering wheel angle is tabular and Gaussian respectively.

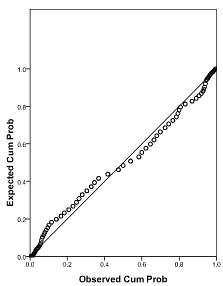


Fig. 6. The P-P plot of steering wheel angle

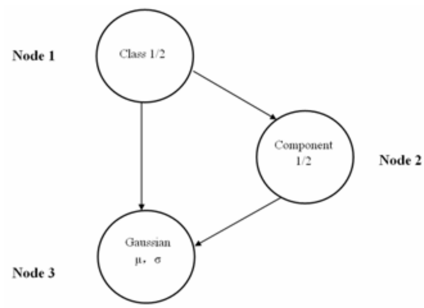


Fig. 7. The graph structure of BN

The jtree_inf_engine[p] is chose as the inference engine. The node size of driver fatigue level and steering wheel angle is 2 and 12 respectively. 500 samples are utilized to train the BN model. The iteration number of EM algorithm is set to 10 and the stopping criterion is 0.01. After training, the parameters of BN are determined. Based on the BN model, the driver fatigue level can be evaluated. Fig.8 shows the training procedure.

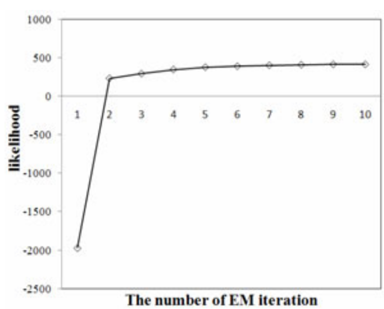


Fig. 8. The training of GMM

Table 2. The evaluation result

Original data/Group	Test Result		
	alert	drowsy	Correct ratio/%
50(alert)	41	9	82
50(drowsy)	12	38	76

5 Discussion and Conclusion

After the BN model is established, another 50 experiment data from alert and drowsy state are chose to evaluate the accuracy. Tab.2 shows the evaluation result. The model identified 41 out of a total of 50 alert samples and 38 out of a total 50 drowsy samples. So the accuracy of the model is about 79%. In this paper, the steering wheel angle is chose as the index to evaluate the driver fatigue level based on BN method. The experiment results show that the model is efficient and practical for fatigue level evaluation. However, the manipulation of steering wheel is greatly influenced by the individual habits, so the model that only considering this source data is not precise enough. The model incorporated multi-sources will be studied in the future.

References

[1] Mao, Z., Chu, X.-m., Yan, X.-p., et al.: Advances of fatigue detecting technology for drivers. China Safety Science Journal 15(3), 108–112 (2005)
[2] Jap, B.: Using EEG spectral components to assess algorithms for detecting fatigue. Expert Systems with Applications 36(2), 2352–2359 (2009)
[3] Lal, S.K., Craig, A.: A critical review of the psychophysiology of driver fatigue. Biological Psychology 55(3), 173–194 (2001)
[4] Eoh, H.J., Chung, M.K., et al.: Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. Int. J. Of Industrial Ergonomics 35(4), 307–320 (2005)
[5] Luis, M.B., Miguel, A.S.: Real-time system for monitoring driver vigilance. IEEE Transactions on Intelligent Transportation Systems 7(1), 63–77 (2006)
[6] Rongben, W., et al.: Monitoring mouth movement for driver fatigue or distraction with one camera, Washington, DC, United states, pp. 314–319 (2004)
[7] Morad, Y., Barkana, Y., Zadok, D., et al.: Ocular parameters as an objective tool for the assessment of trunk drivers fatigue. Accident analysis and prevention 41(4), 856–860 (2009)
[8] Mohanty, M., Mishra, A., Routray, A.: A non-rigid motion estimation algorithm for yawn detection in human drivers. Int. J. of Computational Vision and Robotics, 89–109 (2009)
[9] Gu, H., Ji, Q., Zhu, Z.W.: Active facial tracking for fatigue detection. In: Proceedings of the Sixth IEEE Workshop on Applications of Computer Vision, Orlando, pp. 137–142 (2002)
[10] Skipper, J., Wierwille, W., Hardee, L.: An investigation of low-level stimulus-induced measures of driver drowsiness. Virginia Polytechnic Institute & State University, Amsterdam (1985)
[11] Siegmund, K., King, G., Mumford, D.: Correlation of steering behavior with heavy truck driver fatigue. SAE transactions 105(6), 1547–1568 (1996)

[12] Eskandarian, A., Mortazavi, A.: Evaluation of a smart algorithm for commercial vehicle driver drowsiness detection[C]//Intelligent Vehicles Symposium, pp. 553–559. IEEE Press, Istanbul (2007)
[13] Hong, J.E., Min, K.C., Seong-Han, K.: Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. Int. J. of Industrial Ergonomics 35, 307–320
[14] Heckerman, D.: A tutorial on learning with Bayesian networks. In: Jordan, M. (ed.) Learning in Graphical Models, MIT Press, Cambridge (1998)
[15] http://en.wikipedia.org/wiki/Bayesian_network
[16] Bilmes, J.A.: A Gentle Tutorial of the EM Algorithm and its Application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models. Technical Report, University of Berkeley, ICSI-TR-97-021 (1997)
[17] Moon, T.K.: The expectation-maximation algorithm. IEEE Signal Processing Magazine, 47–70 (November 1996)