EEG Sensor Based Semi-Supervised Inattention Prediction Framework For Unmanned Aerial Vehicles

Yerim Choi*, Jonghun Park†
Department of Industrial Engineering
Seoul National University
Seoul, Republic of Korea
Email: *ian4@snu.ac.kr, †jonghun@snu.ac.kr

Dongmin Shin
Department of Industrial and Management Engineering
Hanyang University
Ansan, Republic of Korea
Email: dmshin@hanyang.ac.kr

***Abstract*—With the advance in sensor devices, electroencephalography (EEG) can be unobtrusively collected enabling the inattention prediction of unmanned aerial vehicle (UAV) operators, which is one solution for reducing the high accident rate of UAVs. Several studies using statistical learning methods on EEG data have shown satisfactory results. However, it is almost impossible to obtain accurate training data containing attention status labels due to the absence of standardized measure for the attention status. Therefore, in this paper, we propose a semi-supervised inattention prediction framework which does not require training data nor any prior information by utilizing the fact that operators keep their attention at the beginning of a task and adopting a cumulative sum algorithm to detect the duration. Moreover, weighted dissimilarity measures are applied to enhance the prediction performance of the proposed framework. From experiments conducted on real-world datasets, the proposed framework showed promising results.**

Keywords–EEG sensor; Inattention prediction; Semi-supervised learning; Cumulative sum algorithm;Weighted dissimilarity measures.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) are known for their high accident rate, which is ten to hundred times higher than that of manned ones [1]. One of the reasons for the high accident rate is the detached cockpits of UAVs, causing frequent inattention of operators [2]. Inattention refers to the status where an operator fails to keep her/his focus on the involved tasks due to external or internal stimuli such as fatigue. Therefore, the accident rate of UAVs can be reduced by predicting the inattention of operators and inducing them to keep their attention.

Among many efforts to predict operators' inattention, electroencephalography (EEG) based statistical learning methods are widely used in various domains including car driving [3] as well as unmanned aerial vehicle maneuvering [4] with satisfactory performances. Particularly, EEG is suitable for inattention prediction of the UAV operators during maneuvering since it can be obtained in less intrusive manner [5] in real time with minimum bias caused by external conditions. Moreover, adopting statistical learning methods is superior to other methods including index based methods [6] or observation based methods [7] in the fact that they enable personalized prediction without human interventions.

Most statistical learning based inattention prediction methods adopt supervised methods such as support vector machines [3] and hidden Markov models [8], which require training data, which is composed of EEG vectors and corresponding attention status labels of an operator. Labels indicate whether the operator is focused or not during the generation of the corresponding EEG vector. Attention status labels used in previous studies are earmarked by utilizing additional information with imperfect assumptions due to the absence of standardized measure of inattention [9]. For instance, Choi et al. [8] assumed that an operator keeps attention while performing more difficult tasks and labeled EEG generated during performing easy task as inattention status. Several studies assumed that the physical behaviors of operators indicate their attention status and used them as labels. However, these labeling techniques may cause performance degradation since the prediction performance of supervised methods depends on the accuracy of training data. On the other hand, unsupervised methods which do not require labeled data are generally known to show insufficient performances.

To overcome the supervised methods' necessity of training data and unsupervised methods' low performance quality, semi-supervised methods, in which a little portion of labeled data or prior knowledge are used to enhance prediction performances, are proposed [9], [10]. Shi et al. [9] utilize two prior knowledge to classify sleep stages of subjects, one of which are extreme stage labels, which are relatively easy to obtain, and another one is stage changing patterns. Choi et al. [10] assume a certain duration of operators' attention from the beginning of tasks and different contributions of frequency bands depending on attention status, both of which are stated in previous literature. Prior knowledge adopted in both studies are still costly to obtain and require human interventions for determining parameters.

To this end, we propose a semi-supervised framework for inattention prediction of UAV operators, where human interventions or additional information usages are minimized. The same assumptions used in [10] are adopted, which are that operators tend to keep their attention for a certain duration from the beginning of tasks [11] and that contributions of frequency bands differ depending on the attention status. Unlike the previous work, additional methods are employed for automatic parameter determination.

Specifically, inattention prediction is performed by using constrained k-means algorithm [12], which keeps a small portion of labeled data unchanged throughout the clustering procedure. As the small portion of attention labels, instances of a certain duration from the beginning of maneuver are used. The duration is automatically determined by conducting the cumulative sum (CUSUM) algorithm for variance change detection [13], by which unusually fluctuation of EEG is detected. Moreover, weights of the four frequency bands

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according to attention status are learned during the clustering procedure by using the weighted dissimilarity measures [14], which determine different weights scheme of features for each cluster.

The rest of paper is organized as follows. In Section 2, the proposed inattention prediction framework for UAV operators is introduced, and its components are presented in detail. Then, performances of the proposed framework are evaluated by using real-world dataset in Section 3, and the paper is concluded in Section 4.

II. Inattention prediction Framework for UAV operators

A. Problem definition

In this paper, we attempt to predict the attention status of an UAV operator by utilizing EEG generated from the operator while maneuvering. Specicially, an EEG sequence of an operator, acquired during performing a task, is denoted by $E = \{\mathbf{e}_n | n = 1, \cdots, N\}$, where $\mathbf{e}_n =< e_{n,m} >$, $m = 1, \cdots, 4$, is the n-th EEG vector composed of $e_{n,m}$, a value of the m-th feature, and N is the total number of EEG vector generated. We note that the four features indicate the four frequencies of EEG power spectral density, alpha (8-12 Hz), beta (13-30 Hz), delta (1-3 Hz), and theta (4-7 Hz), obtained by performing wavelet packet decomposition [15] on orginal EEG signal.

The purpose of the proposed framework is to determine the attention status of $\mathbf{e}_n$. Label matrix, $L = [l_{k,n}]$, is a 2-by-N integer matrix, where $l_{k,n}$ indicates whether $\mathbf{e}_n$ is generated during attention status or inattention status, and it can have two values 1 or 0, and $\sum_k l_{k,n} = 1$. If $\mathbf{e}_n$ is generated during the attention status, $l_{1,n}$ is 0 and $l_{2,n}$ is 1, otherwise $l_{1,n}$ is 1 and $l_{2,n}$ is 0.

B. Framework overview

In this section, the proposed inattention prediction framework is introduced. Figure 1 shows an overview of the framework. First, an operator's EEG data is collected using an EEG acquisition device, and, then, a portion of the collected data is labeled by conducting the CUSUM algorithm. The portion of labeled data and the rest of unlabeled data are clustered according to attention and inattention status, and, at last, when new EEG vector of the operator is given, the attention status of the operator during generation of the vector is predicted by using the clustering results.

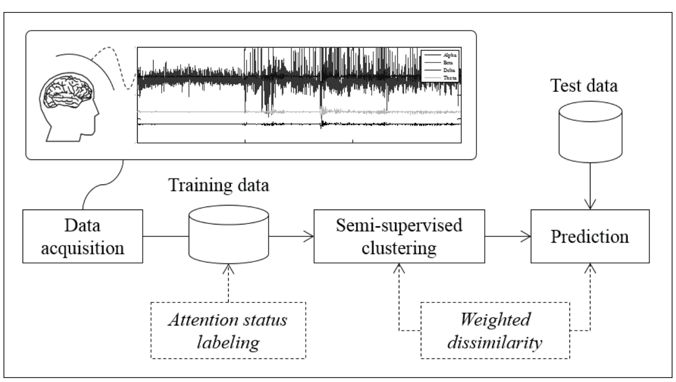

Figure 1. Overview of the proposed framework.

C. Attention labeling using the CUSUM algorithm

To detect the duration, the CUSUM algorithm is adopted, a well-known parameter change detection method for time series data. Particularly, change in variance is detected since there exists a large fluctuation in variance when inattention status occurs as shown in the EEG example from Figure 1. We denote the time, considered as a point where attention is sustained, by d which stands for the duration and call it duration in the rest of the paper.

There exist four time series data, representing the four frequency bands, so that we separately detect their durations and use the minimum value, obtained by (2).

$$d = \min d_m, \ m = 1, \cdots, 4 \tag{1}$$

where d_m is a detected duration of the m-th feature, and it is calculated by (2).

$$d_m = \arg\max_t |D_{t,m}|, \tag{2}$$

where $D_{t,m}$ is defined as (3).

$$D_{t,m} = \frac{\sum_{n=1}^{t} e_{n,m}^2}{\sum_{n=1}^{N} e_{n,m}^2} - \frac{t}{N}, \tag{3}$$

D. Inattention prediction using constrained k-means with weighted dissimilarity measures

Using the duration as a small portion of labeled data, constrained k-means [12] is adopted for the proposed semi-supervised inattention prediction. Additionally, different weights of the four frequency bands are learned according to clusters, attention or inattention, by employing the dissimilarity measures [14]. The proposed algorithm combining the above two methods is in the form of the expectation and maximization scheme [16] as shown in Figure 2.

Input: E, d, $maxIter$
Output: L, C, W
  $t \leftarrow 1$
  $c_{1,m} \leftarrow \frac{1}{d-1} \sum_{n=1}^{d-1} e_{n,m}$
  $c_{2,m} \leftarrow n$
  repeat
    if $n < d$ **then**
      $l_{2,n}^{(t+1)} \leftarrow 1$ and $l_{1,n}^{(t+1)} \leftarrow 0$
    else
      determine $L^{(t+1)}$ for $n = d, \cdots, N$ and $k = 1, 2$
    end if
    determine $C^{(t+1)}$ for $k = 1, 2$ and $m = 1, \cdots, 4$
    determine $W^{(t+1)}$ for $k = 1, 2$ and $m = 1, \cdots, 4$
    $t \leftarrow t + 1$
  until $(t = maxIter)$ || (Equation (4) converges)

Figure 2. Pseudo-code of the inattention prediction algorithm combining constarined k-means with weighted dissimilarity measures.

In Figure 2, C represents a 2-by-m matrix, $m = 1, \cdots, 4$, whose elements are $c_{1,m}$ and $c_{2,m}$ indicate the centroid of inattention and attention cluster, respectively. W is also a 2-by-m matrix, and its element, $w_{k,m}$ is a weight of the m-th feature for the k-th cluster. The three determination process of L, C, and W is to minimize the objective function shown in (4).

$$F(E, L, W, C) = \sum_{k=1}^{2} \sum_{n=1}^{N} \sum_{m=1}^{4} l_{k,n} w_{k,m} s(c_{k,m}, e_{n,m}), \tag{4}$$

where $s(c_{k,m}, e_{n,m})$ is a similarity measure between $c_{k,m}$ and $e_{n,m}$, calculated by (5).

$$s(c_{k,m}, e_{n,m}) = |c_{k,m} - e_{n,m}|^2 \tag{5}$$

Detailed information of the determination process can be found in [14].

III. Experiment

A. Data acquisition

To evaluate the performances of the proposed inattention prediction framework, real-world datasets were collected. Four subjects, including a female and three males, maneuvered a flight simulator called Microsoft Flight Simulator X™ [17], which provides tasks and environments similar to those of actual UAVs, using joysticks which are also similar to the controllers of UAVs. Each subject performed a task of maneuvering an UAV from Kagoshima, Japan to Gimhae, Korea for three times in two days with enough rest to avoid fatigue.

A snapshot of data acquisition using the equipments mentioned above is shown in Figure 3. We used a commercial EEG acquisition tool, Emotive™ EPOC [18]. Using Emotive™ EPOC, EEG was collected from 14 channels according to the international 10-20 system at frequency of 30 Hz and bandwidth between 0.2 Hz and 45 Hz.

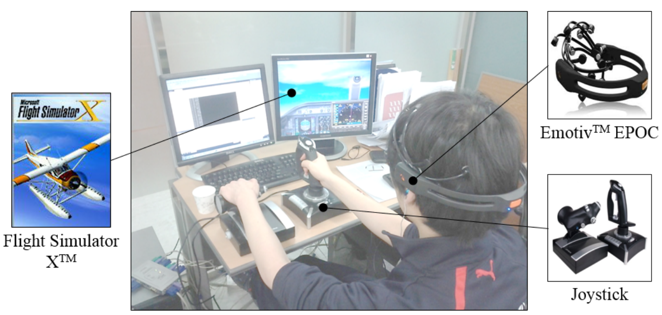

Figure 3. Snapshot of data acquisition procedure by using Emotive™EPOC, joysticks, and Microsoft Flight Simulator X™.

After conducting manual inspection for noise reduction, averaged and normalized magnitudes (in microvolts) across the 14 channels of the four frequency bands were used in the experiments. Subjects were asked to keep certain levels of velocity and altitude while maneuvering, and we assumed that the periods where a subject failed to keep the given standards are the inattention periods of the subject. We note that the information of inattention period only used for model validation purpose.

B. Experiment setting

According to the detection methods for attention durations and weights, nine different models, UM, GW, LW, GD, GWGD, LWGD, DD, GWDD, LWDD, were involved in the experiments. The first three columns in Table II show names and characteristics of the nine models. 'Non' indicates that the models do not utilize any duration or weights for inattention prediction, 'Given' indicates that the models uses the given values of durations or weights, and lastly, 'Detected' or 'Learned' indicates that the model uses detected durations or learned weights by performing the CUSUM algorithm or the weighted dissimilarity measure, receptively.

Among the nine models, UM is one that previously exists and the others where duration and weight are utilized are ones that proposed in this paper. Specifically, in the experiments, 5 minutes of duration and weight scheme (1, 2, 1, 1) for (delta, theta, alpha, beta) were used. Those numbers are ones that have proven to show the best performance by comparing a small set of values in the previous study [10], and, also, theta wave is known to be closely related to sleep states. We note that, unfortunately, a previous inattention prediction method based on supervised and semi-supervised approaches cannot be implemented since we assumed that there is no labeled data for training.

As an evaluation criterion, we employed accuracy which is widely used in statistical learning domain [19]. Accuracy is calculated by (6).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}, \tag{6}$$

where TP, FP, FN, and TN receptively represent the number of true positive, false positive, false negative, and true negative instances as shown in Table I. In addition, all experiments are repeated for ten times, and the results are averaged to minimize randomness.

TABLE I. Confusion matrix for inattention prediction.

	Predicted attention	Predicted inattention
Actual attention	True positive (TP)	False negative (FN)
Actual inattention	False positive (FP)	True negative (TN)

C. Experiment results

In this section, experiment results of the proposed inattention prediction framework are presented. Table II shows the summary of the performance comparison results among the nine models. On the average, LWGD model performed the best with an accuracy of 79.71%, while UM model performed the worst with an accuracy of 54.48%. In most cases, better results can be obtained when the attention status labels for the durations or the weights of four frequency bands are used for the inattention prediction.

In addition, prediction accuracies varies among subjects. For instance, while the best accuracy of Subject 4 is 78.00%, that of Subject 3 is 84.37%, and across all subjects, Subject 4 shows the worst accuracies for all models. This implies that for some operators, the proposed framework may not work satisfactorily, and, therefore, additional care should be given for such operators.

By comparing results of models GD and DD, where GD uses a given duration of 5 minutes for all subjects and DD uses a detected duration for each subject and trial, it can be said that prediction quality enhances when using a detected duration with an exception of Subject 3. Moreover, the effectiveness of learning weights varies among subjects, although for most cases using learned weight enhanced the performances. Therefore, in-depth experiments and explorations on the results should be conducted to show appropriateness of the proposed method.

IV. Conclusion

In this paper, an inattention prediction framework for UAV operators using statistical learning methods on EEG

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TABLE II. PERFORMANCE COMPARISON RESULTS OF THE NINE MODELS ACCORDING TO THE FOUR SUBJECTS IN TERMS OF ACCURACY (IN PERCENT).

Duration	Weight	Model	Subject 1	Subject 2	Subject 3	Subject 4	Average
Non	Non	UM	48.07	65.97	59.64	44.23	54.48
	Given	GW	50.47	62.18	73.31	44.48	57.61
	Learned	LW	47.46	61.93	57.49	48.46	53.83
Given	Non	GD	77.41	78.56	82.07	75.81	78.46
	Given	GWGD	78.56	78.89	81.89	76.67	79.00
	Learned	LWGD	80.15	78.93	84.32	75.41	79.71
Detected	Non	DD	77.90	79.07	81.23	77.20	78.85
	Given	GWDD	78.36	78.92	82.62	77.59	79.37
	Learned	LWDD	77.82	77.97	84.37	78.00	79.54
		Average	64.86	71.97	73.65	66.67	69.29

data is proposed. Particularly, it is in the form of a semi-supervised method by utilizing the fact that operators keep their attention at the beginning of tasks to address the problem of no unified attention standard. To minimize human interventions, an automatic method for detecting attention duration, called the CUSUM algorithm, is adopted, and the weighted dissimilarity measures, where weights of four frequency bands are separately learned depending on cluster during clustering process, are applied to further enhance the performances of the proposed method.

For the future work, we plan to conduct in-depth experiments using diverse settings such as durations and weights. Moreover, for the practical usage, advanced methods for both detecting duration and learning weights should be developed to improve accuracy of current model. Eventually, adoption of the inattention framework to a real-world situation will contribute to the lowering the UAV's accident rate and enhancing UAV operator's safety.

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