Research on pilot perceived intention method based on EEG and visual fixation fusion

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Research on pilot perceived intention method based on EEG and visual fixation fusion

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Abstract. Situational awareness is the ability of pilots to master flight status, which is of great significance to aviation flight safety and flight effect. According to the information processing model, the pilot's main steps of processing information are feeling, perception and execution. There are many problems in situation awareness analysis guided by visual gaze, such as large analysis deviation and high delay due to various influencing factors and complex characteristics. In order to solve this problem, this paper proposes a situation awareness assessment method based on artificial intelligence neural network and integrating visual gaze and flight control. Firstly, this paper carries out simulated flight training experiments for flight cadets, and collects the data of eye movement, line of sight tracking, flight control and flight parameters of pilot cadets. Then, aiming at the flight subjects, a situation awareness analysis method based on events is established, and the situation awareness state in the experiment is evaluated and analyzed through the flight parameter data. Then, the visual gaze and flight control data are sliced in the unit of situational awareness events, and the data set is constructed. Finally, this paper designs a multi-channel sequence data classification and analysis model integrating transformer, in which the situation awareness characteristics of visual gaze and operation behavior are analyzed through the attention mechanism. The experimental results show that the accuracy of situation awareness classification of the designed neural network model to the experimental data set is 96%, and can classify and evaluate the pilot's situation awareness state in 5 seconds.

Keywords:EEG, Visual perception, Neural network, Intention analysis

1. Introduction

Situational awareness in the sense of modern aviation was proposed by Endsley in 1995 [1], also known as situational awareness and situational awareness. Situational awareness is the individual's perception, understanding and prediction of various environmental elements in a specific time and space. According to the human information processing stage model, the pilot information processing process is simplified into three steps, namely feeling, perception and execution [2]. The feeling is that the pilot turns his attention to the processing object; Perception is the pilot's recognition, judgment and positioning of the processing object; Execution is the pilot's final response to the processing object and carries out interactive operation on the aircraft [3]. At present, researchers have realized the significance of pilots' situational awareness for aviation flight safety. For example, the French aviation accident investigation bureau suggested that relevant situational awareness research be integrated into the pilot system to improve the cockpit procedure [4].

Situation awareness analysis methods are generally divided into direct detection methods and indirect detection methods. The direct method is mainly based on observation, investigation and inquiry, while the indirect method is to realize the assessment of situation awareness through pilot behavior, physiological response and flight effect assessment [5] [6]. In the direct method, the inquiry evaluation is generally based on the pilot's memory, which often needs to interrupt the flight experiment, and the observation evaluation will be affected by the cognitive deviation of the observer, which will affect the evaluation results. The indirect method is based on sensors such as eye tracker and flight data to realize the assessment of situation awareness through algorithm. The indi-

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rect method has the ability to be applied to actual flight scenes and provides high-precision situation awareness assessment and analysis [7].

In aviation flight, 90% of the pilot's information comes from vision [8]. Visual gaze analysis based on eye tracking technology is an effective indirect analysis method to study situational awareness [9]. For example, Paletta L, Dini A and other eye movement equipment carry out situation awareness analysis based on visual gaze [10]. K. Moore et al. Studied AOI region of interest as an analysis method of visual gaze information for situation awareness [11]. It is generally believed that the longer you focus on an AOI area, the stronger your situational awareness [12] [13] [14]. Integrated into flight analysis, the research of brams s and others on cockpit fault detection shows that compared with non pilots, pilots have a more efficient way to obtain visual information through the overall model of long-term working memory theory, information simplification hypothesis and image perception, which proves that visual behavior can show the ability level of pilots [15]. Lounis C et al. Studied visual information acquisition, gaze distraction and gaze patterns among pilots with different technical levels through eye movement feature indicators, which further showed that more professional pilots have higher perception efficiency, more effective attention distribution patterns and more complex and fine visual scanning patterns [16].

In the cockpit, barometric altimeter, airspeed and Mach number meter, vertical speed / sideslip meter, attitude guidance indicator (ADI) and wireless electromagnetic heading indicator are important instruments for pilots to establish flight situation awareness. The pilot obtains the information on the instrument by staring. In manual flight without autopilot, the pilot needs to repeatedly check the instrument and refresh the flight situation information to maintain the stability of flight performance. Relevant research shows that once pilots have no redundant cognitive ability, no matter whether they are willing to invest more energy in the task or not, any increased task demand will gradually reduce the pilot's performance [17] [18]. Among them, the research of rainieri g and others on eye movement, line of sight analysis and psychological load evaluation of different helicopter pilots during landing further shows that the performance and perceived mental load of pilots change with the change of professional knowledge and flight conditions [19].

The above research deeply discusses the relationship between pilots' visual gaze and situational awareness, and realizes accurate situational awareness assessment. However, most of these studies evaluate and analyze the situation awareness of pilots in flight after the experiment. At the same time, due to the complexity of pilot state, there is uncertainty in the analysis of simple visual gaze channel data. That is, the situation awareness of pilots cannot be determined from a single visual gaze behavior. It is necessary to expand the analysis window for statistical analysis to evaluate the situation awareness, which leads to high delay of analysis methods and lack of real-time analysis ability.

In order to solve the above problems, a situation awareness analysis method integrating visual gaze and flight control is proposed in this paper. The situation awareness classification and analysis of complex data is realized by integrating transformer's artificial intelligence neural network model. The basic process of this method is as follows:

i. Set flight subjects, carry out simulated flight training experiments, and synchronously collect pilot visual gaze, flight control and flight parameter data.

ii. According to the flight evaluation criteria of flight training subjects and combined with the flight parameter data, an event feature and segmentation method is proposed, and then the situation awareness states in different periods of flight experiment are classified and analyzed in the unit of events. Among them, this paper takes altitude situational awareness in five side flight as the research object to evaluate the altitude maintenance ability of flight cadets in flight training experiments.

iii. Slice the visual gaze and flight control corresponding to the time of the event, and construct the data set with 5 seconds as the analysis window. A multi-dimensional sequential data neural network situation awareness classification and analysis model integrating transformer is established, and finally the model training experiment is carried out.

This method solves the classification problem of situation awareness related patterns of complex visual gaze and flight control data by integrating transformer artificial intelligence neural network model. Transformer's attention mechanism can solve the performance problem of feature analysis in multi-dimensional sequence data. Finally, the model trains the self built data set to achieve 96% accuracy. This method provides a reference for the situation awareness assessment of multi-dimensional data, and is expected to be applied to the field of pilot selection and training and pilot real-time detection in the future, so as to achieve the goal of improving pilot skills and safety.

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2. Material and Methods

2.1. Method Principle

Pilot Perception Analysis Based on EEG, visual gaze and flight control is an indirect detection method [18]. The data acquisition of indirect analysis method is carried out simultaneously with the pilot's flight, and the data analysis process, whether in real time or afterwards, will not affect the pilot in the experiment. In real-time analysis, we can only analyze through the generated data, and the limitations of the data will directly affect the accuracy and real-time of the analysis method. The pilot perceived intention analysis method in this paper makes up for the limitation of gaze data through EEG data. Before analyzing perceived intention through EEG data, it is necessary to build a computer sample data set, in which each EEG data sample has a clear label of perceived intention.

The analysis method flow constructed in this paper is shown in Figure 1. Through the post analysis of the flight experiment data, four perceived intention events of altitude, speed, attitude and heading are selected from the flight experiment data. Visual fixation and flight control data are the main basis for the qualitative analysis of perceived intention events. Then, the EEG data corresponding to the occurrence time of perceived intention event is taken as the sample, and the category of perceived intention event is taken as the label to form the EEG data set. Finally, the deep learning neural network model is designed and established, and the EEG data set is used for training experiment.

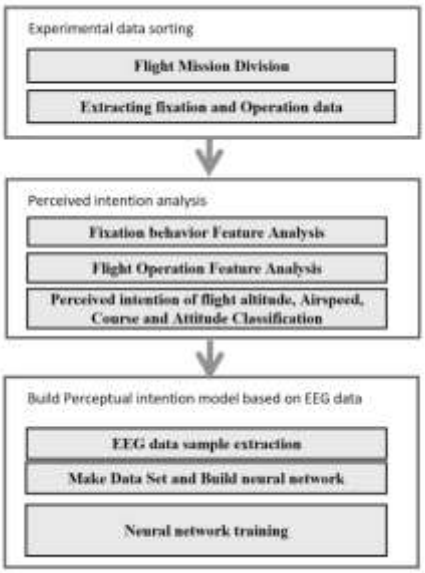

Fig. 1. Basic flow of experimental analysis method

2.2. Pilot perceived intention analysis based on visual gaze and flight control

1)Visual fixation data features

The experimental platform of this paper displays the aircraft cockpit on the main display with a fixed angle of view. The infrared non wearable eye tracker can obtain the fixation and landing coordinates of the subjects on the main display in real time. In order to simplify the analysis, this paper adopts the region of interest (AOI) analysis method, that is, the image in the main display screen is divided into regions according to the information category [19]. When the gaze resides in the region of interest, it is considered that the pilot has obtained the main perceptual information in the region. Region of interest analysis does not need to specifically analyze the fixation point, and how to obtain information through the text pointer details in the fixation area. As shown in Figure 2, AOI areas containing key flight information in flight include attitude meter, vertical speedometer, altimeter, airspeed meter and magnetic heading table. These AOI areas are divided according to different color codes in the template.

Fig. 2. Simulate the AOI area template of the flight cockpit. ADI: attitude, RMI: electromagnetic heading indication, ADF: automatic lateral instrument, SPD: airspeed meter, ALT: barometric altimeter, VSI: vertical speedometer.

In this paper, when AOI gaze analysis is carried out, the visual gaze data will be divided into gaze events of different lengths, in which the gaze from entering an AOI area to moving out of the AOI area is a gaze event. In order to study the pilot's acquisition of instrument information in each event of gazing at the instrument, this paper takes the gazing drift rate and gazing time as the main analysis data. It is generally considered that when the time of gazing at an instrument AOI area is long enough and the gazing drift rate is small, it can indicate that the pilot has read the information from the instrument.

The fixation drift rate is the drift speed of the fixation point on the screen, in pixels per second. In order to facilitate the fusion with other types of data, we need to normalize the global contrast of the fixation drift rate. Let $V_{eye}(t)$ be the gaze drift rate at time t. since the sampling rate of the eye tracker is 100Hz, each group of data is the average velocity of gaze drift within 10ms. As shown in equation 1, the fixation drift data set of all experiments is V_{eye}, and the standardized data $Q(t)$ of fixation drift rate at time t is obtained.

$$Q(t)=\frac{v_{eye}(t)-\frac{1}{n}\sum_{k}^{n}V_{eye}(k)}{\sqrt{\frac{1}{n}\sum_{i}^{n}\left(V_{eye}(i)-\frac{1}{n}\sum_{k}^{n}V_{eye}(k)\right)^{2}}} \tag{1}$$

Then, V_{eye} is brought into the equation to obtain the standardized data Q of the whole experiment, and the maximum and minimum values of the standardized data Q are calculated. Finally, the global contrast normalized data of gaze drift rate at time t are obtained.

$$N_{eye}(t)=\frac{Q(t)-\min(Q)}{\max(Q)-\min(Q)} \tag{2}$$

Each fixation event contains a set of visual fixation drift rate sequence data. In order to take the fixation drift rate as the judgment basis for the acquisition of fixation information, we extract the differential entropy feature of the fixation drift rate data in each fixation event. As shown in equation 3, firstly, calculate the average power density PSD for the fixation drift global contrast normalization sequence data staring at an AOI region, where FS is the frequency. Then, as shown in equation 4, the differential entropy DE of gaze drift rate is calculated by PSD.

$$PSD_{eye}=\frac{\sum_{i=a}^{b}abs\left(N_{eye}(i)\right)}{\frac{1}{fs}(b-a)} \tag{3}$$

$$DE_{eye}=\log^{2}\left(PSD_{eye}\right) \tag{4}$$

According to the characteristics of differential entropy, the lower the gaze drift rate and the smaller the average power density, the smaller the differential entropy. When the differential entropy eigenvalue of gaze drift rate of a gaze event is small, even if the gaze time is not long compared, it can also show that the pilot gazed at the instrument and has a high probability to obtain the instrument information.

2)Flight control data characteristics

The main control equipment of the aircraft are joystick, foot rudder and throttle, in which there are four control degrees of freedom, and the output data of each degree of freedom is axis data. In our experimental platform, the control axis data is also a 100Hz time series data. Due to the characteristics of cruise flight, the pilot's adjustment of the lever amount of the control lever is based on the correction of the flight situation. Therefore, the flight control data in the cruise flight section has more obvious characteristics of perceived intention.

In this paper, the flight control characteristics are expressed by signal power. As shown in equation 5, the characteristic calculation is carried out for the change rate of each longitudinal axis, where a and b are the start and end time of the sample, $Oper(t)$ is the axis change rate, and $Oper2(t)$ is the signal power.

$$E_{oper}=\int_{a}^{b}Oper^{2}(t)dt \tag{5}$$

The energy characteristics are reflected in the sample sequence data. When the pilot controls the rocker, the relevant control axis data will show large energy change characteristics during maneuver adjustment.

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3) Analysis of perceived intention characteristics

As shown in Figure 3, the perceptual intention analysis of a visual gaze event is to judge by fusing the characteristics of gaze data and manipulation data, so as to solve the problem of uncertainty in perceptual intention analysis of simple gaze data. When the pilot looks at a flight instrument and performs corresponding flight operations, the perceived intention category of the visual gaze event can be defined. This paper aims at four kinds of perceived intentions in basic flight: altitude, airspeed, attitude and heading.

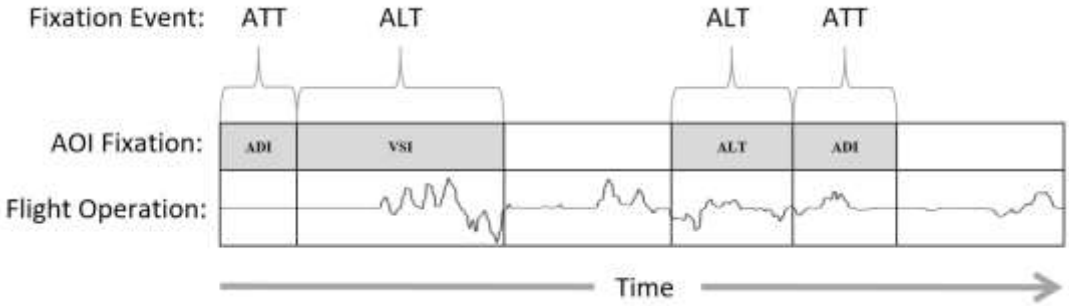

Fig. 3. Analysis of perceived intention based on gaze events

According to the research on fixation time of different reading types, as shown in Table 1, if the human eye looks at the AOI area for more than 200ms, it can indicate that the information in the AOI area has been read [20]. At the same time, the lower the eigenvalue of differential entropy of gaze drift rate, the more stable the gaze is, indicating that the pilot is actually reading the information on the instrument. As shown in Figure 4, sort the gaze differential entropy characteristics of events in AOI area of gaze altimeter in flight experiment, and observe the change trend of visual gaze time. After smoothing the gaze time curve, it can be seen that when the eigenvalue of gaze drift differential entropy is high, the gaze time shows an overall downward trend.

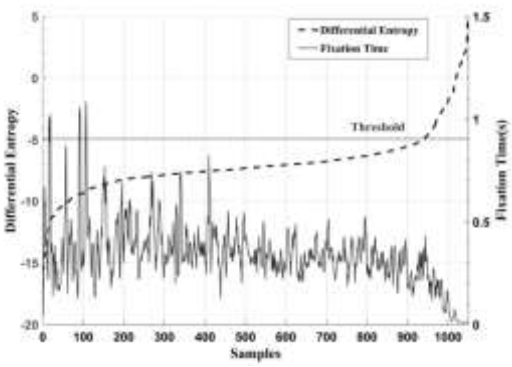

Fig. 4. Characteristics of visual gaze differential entropy.

Table 1

fixation duration of different reading types

Fixation type	fixation time(ms)
Silent reading	225 – 250
Oral reading	275 – 325
Scene perception	260 – 330
Visual search	180 – 275

Then, taking the manipulation data as a reference, it is clear that the visual gaze of the reading instrument is driven by the corresponding perceptual intention. Taking altitude perception as an example, as shown in Figure 5, the pilot looks at the statistical relationship between the gaze drift rate of the altimeter and the energy characteristics of the pitch axis control signal. The energy characteristics analysis window of the control signal calculates the control data from the beginning of gaze to 2S later. Similarly, airspeed is related to throttle valve axis data, attitude is related to control pitch axis and roll axis, and heading is related to control lever roll axis data.

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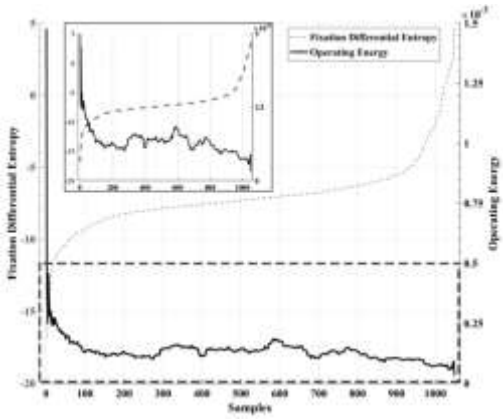

Fig. 5. Energy characteristics of flight control quantity of high pitch

Sort out the instrument gaze and control data of pilots' perception of altitude, airspeed, attitude and heading. Set the classification threshold of perceived intention as shown in Table 2, that is, when the pilot looks at an instrument AOI area in flight and meets the corresponding gaze duration, gaze differential entropy characteristics and corresponding control data energy characteristics, the perceived intention category of perceived gaze behavior can be determined. The EEG data of 1 s from fixation were intercepted as training samples.

Table 2

Fixation duration of different reading types

Perception type	Operating energy characteristic threshold	Fixation time(ms)	Gaze drift velocity differential entropy
Altitude	0.00009	500	-5
Airspeed	0.00013		
Attitude	0.00004		
Course	0.00004		

2.3. EEG data preprocessing and feature analysis

This paper uses bitbrain's 32 lead semi dry electrode EEG with a sampling frequency of 256Hz. The electrode of EEG EEG is attached to the scalp surface. As shown in Figure 6, the position distribution of electrodes on the scalp follows the lead scheme formulated by the American Society of clinical neurophysiology, in which 10-10 lead system [21] and 10-20 lead system [22] are used as complementary to assign specific positions to each EEG electrode.

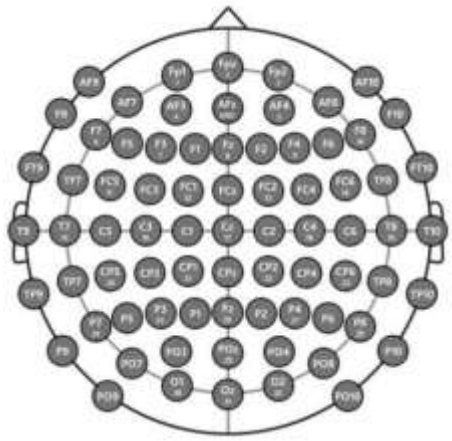

Fig. 6. Location distribution of 10-10 lead EEG electrode lead and 32 lead EEG electrode.

1)EEG electrode signal conversion reference

The intention recognition of EEG is to analyze the event potential activity generated by the brain under specific activities. The data collected by EEG scalp electrode is the potential difference between the acting electrode and the reference electrode. Since muscle activities in other parts of the human body will also produce electrical signals, affecting the potential data collected by EEG scalp electrodes [23], the inactive position is generally selected for the reference electrode, such as Essl.M.et al. Proposed to use FCz electrode as the reference electrode [24], and the earlobe is also a good reference electrode position.

$$V = GX \approx \left(GG_{T10}^{+}\right)V_{T10} \tag{6}$$

2)Filtering and noise reduction

EEG electroencephalograph obtains weak voltage signal generated by weak brain nerve activity through electrode, and its voltage variation is 5-100 μV, vulnerable to environmental electromagnetic interference. After the standardization of EEG data, filtering processing is needed to reduce clutter interference.

If the electrical signal collected by the brain electrode is *Es(t)* and the environmental interference is *Js(t)*, the electrical signal of brain activity is:

$$Bs(t) = Es(t) - Js(t) \tag{7}$$

Interference signals are superimposed by signals from different sources and different frequencies. As shown in Figure 7, the main interference signals are composed of 49~51hz municipal electrical signals and 0.1~1.5Hz respiratory and heartbeat interference signals [28]. Firstly, the mains interference signals *Js1(t)* and *Js2(t)* are obtained respectively through the second-order IIR Notch filter, and then the two interference signals (equation 8) are subtracted from

the original signal to obtain the target EEG signal after interference filtering.

$$Bs(t) = Es(t) - Js_1(t) - Js_2(t) \tag{8}$$

3) Detection area filtering

The filtered EEG signal can be regarded as time series data of 256 frames per second. As shown in Figure 8, Fp1, FpZ, Fp2, AF3 and AF4 in the forehead area are vulnerable to the interference of blinking oculomotor nerve signals. These four electrodes are excluded during analysis. At the same time, according to the actual experimental use, some EEG electrode data with unstable signal caused by poor wearing effect are selectively excluded.

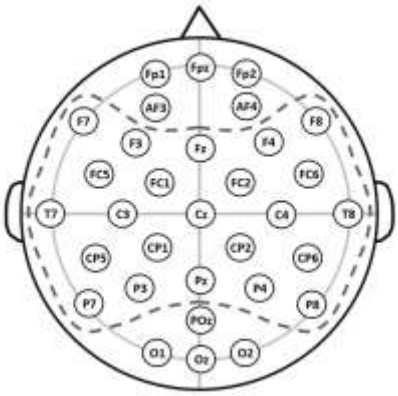

Fig. 7. EEG signal spectrum. a before filtering, b after filtering

2.4. Classification model based on transformer neural network

EEG data is a multi-dimensional time series data. This paper designs a neural network model based on transformer to solve the problem of EEG data classification. Transformer improves the efficiency of algorithm processing complex data analysis and training through self attention mechanism [29]. At the same time, self attention mechanism can express the convolution filter layer of any CNN. As shown in Figure 9, the network model in this paper is composed of three transformer encoders and feature fusion modules.

1) EEG spatiotemporal feature extraction

Set the input EEG data as $\chi = \{x_1^{(j)}, x_2^{(j)}, x_3^{(j)}, ..., x_t^{(j)}\}$, j as the number of electrodes, and t as the time of time series. The EEG data sample in this paper is the 23 conductor data of window 1s, then $t = 256$. The input sequence data of EEG is compared with an initial matrix $M_{m\times n}$ is multiplied to obtain three vectors: sequence data Q, key value K and weight V. Then the attention is calculated as equation 9, and the weight of the EEG sequence data is obtained.

$$A(Q,K,V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{m}}\right)V$$
$$A(q_i,K,V) = \sum_y \frac{\exp\left(\frac{q_i \times k_i^T}{\sqrt{m}}\right)}{\sum_x \exp\left(\frac{q_i \times k_x^T}{\sqrt{m}}\right)} v_y \tag{9}$$

In order to expand the ability of self attention to different location data, transformer adopts the multi head attention mechanism, that is, the Q, K and V vectors of the input data are mapped into different spaces through linear transformation to obtain multiple groups of vector data, calculate the attention of each group of data, and splice the results.

$$MH(Q,K,V) = Concat(H_1,H_2,...,H_h)W^O$$
$$H_h = A\left(QW_h^Q, KW_h^K, VW_h^V\right) \tag{10}$$

In the transformer encoder, the EEG data is input, and the data processed by multiple heads of attention is subjected to dropout and normalization before convolution. The convolution processing is shown in equation 11, (*cx, cy*) is the number of adjacent convolution layers, W is the weight matrix, *fk* is the filter order, and *b* is the offset. As shown in Fig. 5, the attention processed data and the convolution processed data are superimposed on the original input sequence data and output for feature fusion.

$$Conv_{cx,cy}^{fk} = f\left[\left(W^{fk} \cdot x_{input}\right)_{cx,cy} + b_{fk}\right] \tag{11}$$

2) EEG feature fusion classification

After three Transformer encoders and global average pooling processing, the input data is 256 dimensionals feature data with high correlation with perceived intention classification. The feature fusion classification adopts the combination of 128 nodes full connection layer and dropout. Finally, the output data after tensor flattening is the probability value of *label*, and *l* is the classification number.

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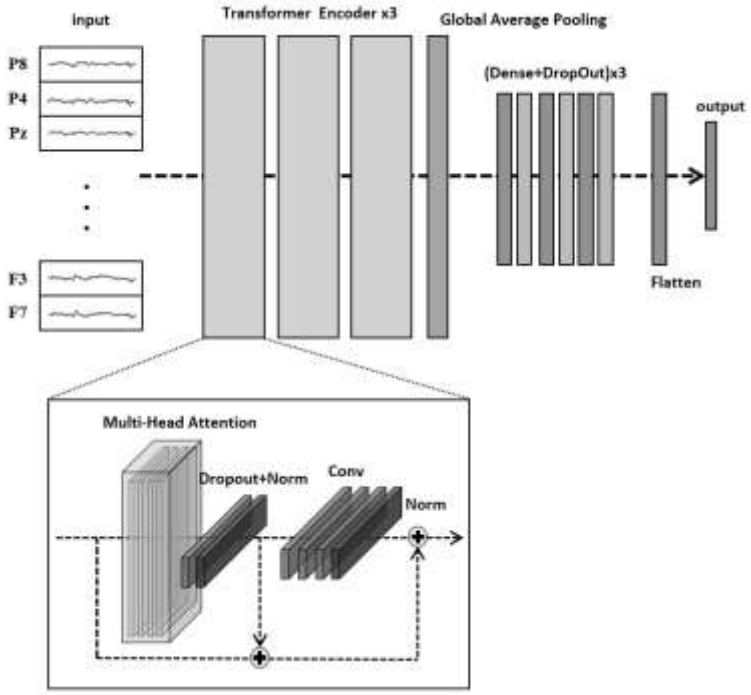

Fig. 8. Neural network model based on transformer

3. Experimental process and result analysis

3.1. Design of simulated flight experiment

In this paper, the test is carried out on a miniaturized simulated flight motion platform, which is composed of motion platform, display, HOTAS rocker and foot rudder. The acquisition equipment includes non wearable eye tracker and 32 lead wearable EEG cap. The simulation model adopts L39C trainer. The experimental training course is five side flight.

Fig. 6. Simulated flight experiment platform

Five side flight requires the pilot to take off and enter the first side, then enter the landing course and landing airport after cruising and four turns. Among them, the heading of the five sides is {095,005,275,185,095}, the cruise altitude is required to be 633m, and the cruise airspeed is required to be between 200kmh and 300kmh.

In the experiment, the reaction time test is carried out at the same time. The test is that a visual target appears at random position and time on the screen, and the pilot completes the experiment by looking at the target. The purpose of this test is to interfere with the pilot by adding random additional work tasks, destroy the flight steady state, and make the pilot maintain the attention and concentration of each flight state.

This paper carries out experiments for flight cadets, aged 24-30. The flight cadets have carried out simulated flight training before the experiment, and have the flight technical requirements to complete the experimental subjects. The experimental equipment is non-invasive and does not harm the human body. It is agreed by the subjects before the experiment.

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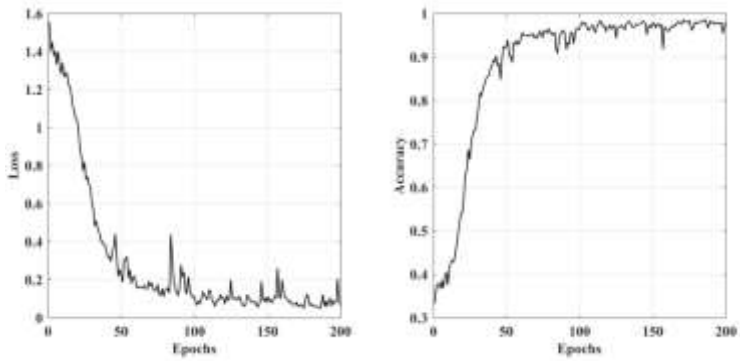

Fig. 8. Training loss rate and accuracy of neural network model

Table 3

Comparison of different subjects and different methods

	Subjects				Average
	A	B	C	D	
Transformer	92.83	91.75	92.07	93.09	92.44
LSTM	85.48	86.01	86.60	86.65	86.19

3.2. Experimental and analytical results

1) Building data sets

In each flight experiment, the flight cadets will carry out multiple five sided takeoff and landing flight exercises. After obtaining the data, firstly, the experimental data are segmented through the flight data to extract the cruise flight phase data. Then, according to the visual gaze attitude meter, altimeter, vertical speedometer, airspeed meter and magnetic heading instrument AOI area gaze events, the pilot's perception intention of altitude, attitude, heading and airspeed is analyzed by fusing the control data within 2S after the gaze event. Extract the event time data of perceived intention. Next, we will talk about the event time data of perceived intention, and intercept the corresponding EEG data 1 s after the start time of gaze event as a sample. Finally, the altitude intention, airspeed intention, attitude intention and heading intention corresponding to the gaze event are used as labels of EEG sample data. At the same time, the EEG samples corresponding to the fixation events in the non flight information related areas of visual fixation are cut as the non perceptual intention samples.

2) Constructing neural network model and training experiment

The multi-dimensional EEG data classification model based on transformer is established, and the data set established by flight experiment data is used for neural network training, as shown in Figure 11. After 200 epoches training, the training accuracy reaches 96% and the loss is reduced to 0.07.

The trained neural network model is tested on the data of four flight cadets, as shown in Table 3. The average accuracy is 92%. The classification accuracy of LSTM method for the data set in this paper is 86%, which shows that the neural network model based on transformer has significantly improved the classification performance.

4. Conclusions

In this paper, visual fixation, manipulation and EEG data are obtained from experiments close to the actual flight. The screening and extraction of EEG intention samples are realized by the fusion of visual fixation, manipulation and flight data. This method ensures that the intention information contained in EEG data is generated by the pilot in response to the actual flight. After the neural network training experiment based on transformer, the classification accuracy of brain inductance can reach 92.44%, which is significantly improved compared with LSTM algorithm.

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This paper takes basic flight training as the experimental subject, and the analysis of perceived intention focuses on the detection of flight basic perception such as altitude, airspeed, heading and attitude. Based on the principle and process of this method, the experimental subjects are modified, which can be extended to the perceptual intention analysis of other objects. Analysis of pilots' adaptation to different flight environments and driving intentions. It provides theoretical and methodological support for pilot condition monitoring and early warning, human-computer intelligent interaction research and application.

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Competing interests

The authors declare no competing non-financial / financial interests.

Availability of data and material

Not applicable

Code availability

Not applicable

Ethics approval

Not applicable

Consent to participate

All authors agreed to participate

Consent for publication

The author confirms:

• that the work described has not been published before(except in the form of an abstract or as part of a published lecture, review, or thesis).

• that it is not under consideration for publication elsewhere.

• that its publication has been approved(tacitly or explicitly) by the responsible authorities at the institution where the work is carried out.

Authors' contributions

All authors contributed to the study conception and design. Conceptualization, methodology, data collection and analysis were performed by [Guangyi Jiang],[Hua Chen],[Changyuan Wang]. Software and Visualization were performed by [Pengxiang Xue]. The first draft of the manuscript was written by [Guangyi Jiang] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

References

[1] Shappell. S, Detwiler. C, Holcomb. K, et al. “Human Error and Commercial Aviation Accidents: An Analysis Using the Human Factors Analysis and Classification System” Human Factors, 2007, 49(2):227-242.

[2] European Aviation Safety Agency, “Notices of Proposed Amendments 2016-03(A). Technical review of the theoretical knowledge syllabi, learning objectives, and examination procedures for air transport pilot licence, multi-crew pilot licence, commercial pilot licence, and instrument ratings”, 2016.

[3] Robert J. K. Jacob,Keith S. Karn, “Eye Tracking in Human-Computer Interaction and Usability Research: Ready to Deliver the Promises”, The Mind’s Eye,2003,(3):573-605.

[4] Lounis. C, Peysakhovich. V, Causse. M, “Visual scanning strategies in the cockpit are modulated by pilots' expertise: A flight simulator study”, PLoS ONE, 2021, 16(2):e0247061.

[5] Koen van de Merwe，Henk van Dijk，Rolf Zon. “Eye Movements as an Indicator of Situation Awareness in a Flight Simulator Experiment”, International Journal of Aviation Psychology, 2012, 22(1):78-95.

[6] Lounis. C, Peysakhovich. V, Causse. M, “Visual scanning strategies in the cockpit are modulated by pilots' expertise: A flight simulator study”, PLoS ONE, 2021, 16(2):e0247061.

[7] Azar. A. T, Balas. V. E, Olariu.T, "Classification of EEG-Based Brain－Computer Interfaces[J]. Springer International Publishing", 2014.

[8] J. Desai, "Electroencephalography (EEG) Data Collection and Processing through Machine Learning", University of Arkansas. 2014.

[9] Perlis. M. L, Smith. M. T, Andrews. P. J, et al, "Beta/Gamma EEG activity in patients with primary and secondary insomnia and good sleeper controls", Sleep, 2001(1):110-117.

[10][10]Kai. K. A , Zhang. Y. C , Zhang. H , et al, "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface", IEEE International Joint Conference on Neural Networks. IEEE, 2008.

`

[11] Roy. Y, Banville. H, Albuquerque. I, et al, "Deep learning-based electroencephalography analysis: a systematic review", Journal of Neural Engineering, 2019.
[12] Borra. D , Fantozzi. S , Magosso. E, "Convolutional Neural Network for a P300 Brain-Computer Interface to Improve Social Attention in Autistic Spectrum Disorder", 2019.
[13] Farahat. A , Reichert. C , Sweeney-Reed. C. M, et al, "Convolutional neural networks for decoding of covert attention focus and saliency maps for EEG feature visualization", Journal of neural engineering, 2019, 16(6):066010.1-066010.14.
[14] Leeuwen. K , Sun. H , Tabaeizadeh. M , et al, "Detecting Abnormal Electroencephalograms Using Deep Convolutional Networks", Clinical Neurophysiology, 2018, 130(1).
[15] Xi. X, Ma. C, Yuan. C, et al, "Enhanced EEG－EMG coherence analysis based on hand movements", Biomedical Signal Processing and Control, 2020, 56:101727-.
[16] D.Borra, Fantozzi.S, Magosso.E, "Interpretable and lightweight convolutional neural network for EEG decoding: Application to movement execution and imagination", Neural Networks, 2020, 129.
[17] Wang. W, "Brain network features based on theta-gamma cross-frequency coupling connections in EEG for emotion recognition", Neuroscience Letters, 2021(1):136106.
[18] K. Moore, L. Gugerty, “Development of a novel measure of situation awareness: the case for eye movement analysis”,Proceedings of the Human Factors and Ergonomics Society-Annual Meeting, vol. 54, no. 19, pp. 1650－1654, 2010.
[19] Dehais. F , Behrend. J , Peysakhovich. V , et al, "Pilot Flying and Pilot Monitoring's Aircraft State Awareness During Go-Around Execution in Aviation: A Behavioral and Eye Tracking Study", The International Journal of Aerospace Psychology, 2017, 27(1-2):15-28.

References

[30] B. Newman and E.T. Liu, Perspective on BRCA1, Breast Disease 10 (1998), 3–10.
[20] Rayner Keith, "Eye movements and attention in reading, scene perception, and visual search", Quarterly Journal of Experimental Psychology, 2009, 62(8):1457-1506.
[21] Seeck M , Koessler L , Bast T , et al, "The standardized EEG electrode array of the IFCN", Clinical Neurophysiology Official Journal of the International Federation of Clinical Neurophysiology, 2017, 128(10):2070-2077.
[22] Rojas G M, Carolina A, Montoya C E, et al, "Study of Resting-State Functional Connectivity Networks Using EEG Electrodes Position As Seed", Frontiers in Neuroscience, 2018, 12:235-.
[23] Sundararajan. A, Pons. A, Sarwat. A. I, "A Generic Framework for EEG-Based Biometric Authentication", Information Technology - New Generations (ITNG), 2015 12th International Conference on. 2015.
[24] Essl. M, Rappelsberger. P, "EEG cohererence and reference signals: experimental results and mathematical explanations", 1998, 36(4):399-406.
[25] Yao, Dezhong, "A method to standardize a reference of scalp EEG recordings to a point at infinity", Physiological Measurement, 2001, 22(4):693-711.
[26] Xu. L, Liao. K, "Understanding the Influences of EEG Reference: A Large-Scale Brain Network Perspective", Frontiers in Neuroscience, 2017, 11:205.
[27] Chella F , Pizzella V , Zappasodi F , et al. "Impact of the reference choice on scalp EEG connectivity estimation", Journal of Neural Engineering, 2016, 13(3):036016.
[28] Teplan. M, "FUNDAMENTALS OF EEG MEASUREMENT M. Teplan", 2002.
[29] Vaswani Ashish，Shazeer Noam，Parmar Niki，Uszkoreit Jakob，Jones Llion，Gomez Aidan N，Kaiser Lukasz，Polosukhin Illia, "Attention Is All You Need". arXiv, 2017.
[31] D.F. Pilkey, Happy conservation laws, in: Neural Stresses, J. Frost, ed., Controlled Press, Georgia, 1995, pp. 332–391.
[32] E. Wilson, Active vibration analysis of thin-walled beams, Ph.D. Dissertation, University of Virginia, 1990

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