Recognition and Dynamics of Changes in the Emotional States of Aviation Personnel in the Context of Aviation Safety Using Markov Chains

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Abstract. Modern aviation safety largely depends on the psychophysiological stability and emotional regulation of aviation personnel. Errors caused by emotional destabilization, stress, and fatigue are among the most common factors leading to incidents in both civil and military aviation. Pilots, air traffic controllers, and onboard operators perform their duties under conditions of high cognitive tension, information overload, and multitasking, where emotional fluctuations directly affect situational awareness, reaction speed, and the adequacy of decision-making. This study is devoted to the development of an integrated model for recognizing and analyzing the dynamics of changes in the emotional states of aviation personnel aimed at enhancing aviation safety. The proposed methodology combines emotion recognition using a convolutional neural network (CNN) with dynamic modeling of transitions between emotional states based on the framework of Markov chains. Seven basic emotions according to Paul Ekman are used as the target categories. The first subsystem the emotion recognition module is implemented using a CNN. Recognized emotions are treated as discrete system states reflecting the internal psycho-emotional condition of the operator. At the second level of the model, a first-order Markov chain is applied to quantitatively describe the probabilities of transitions between emotional states. Each transition probability reflects the temporal dynamics of emotional changes and serves as an indicator of the operator's emotional stability. The proposed Markov model of emotional dynamics provides quantitative and predictive tools for assessing the emotional readiness and cognitive stability of aviation personnel. Integrating the emotion recognition module with probabilistic modeling enables real-time detection of stress growth, prediction of emotional exhaustion, and prevention of conditions that may lead to operational errors or threats to flight safety. In the future, the system is planned to be expanded through the use of non-homogeneous and hidden Markov chains (HMM, NHMM), as well as multi-agent analysis aimed at studying the group emotional synchronization of crews and controllers. Thus, the presented methodology establishes a foundation for next-generation intelligent aviation safety systems, in which human emotional dynamics are treated as measurable, predictable, and controllable variables that directly influence reliability and efficiency in complex human–machine environments..

Keywords: Aviation Safety, Emotion Recognition, Markov Chains, Psychophysiological State, Convolutional Neural Networks (CNN).

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1 Introduction

Aviation safety remains one of the key priorities of the modern aviation industry. Despite the high level of automation, the development of navigation systems, and the improvement of technical regulations, recent studies show that up to 70% of aviation incidents are directly related to the human factor [1]. Psychophysiological resilience of aviation personnel is of particular importance, since pilots and air traffic controllers operate under conditions of high cognitive workload, information saturation, and limited time for decision-making [2].

Emotional instability, stress, and fatigue can significantly reduce the accuracy of perception, reaction speed, and the ability to maintain situational awareness—factors that are critically important for ensuring flight safety. Contemporary research confirms that even moderate changes in emotional state can lead to errors in piloting, navigation, and air traffic control [3]. While fatigue and health monitoring systems are being actively implemented, methods for dynamic analysis of emotional states are still insufficiently applied in aviation practice [4].

The development of artificial intelligence technologies, especially in the field of computer vision, opens new opportunities for automated monitoring of the emotional states of aviation personnel. Face Emotion Recognition (FER) systems based on convolutional neural networks demonstrate high accuracy and robustness in real-world conditions [5]. They make it possible to register emotional reactions in real time, which enables the creation of continuous psychophysiological profiles of operators.

The temporal dynamics of emotions can be effectively described using stochastic models. First-order Markov chains make it possible to quantitatively assess the probabilities of transitions between different emotional states, characterizing the stability of the emotional profile, the likelihood of its degradation, and the risk of forming stress-inducing states [6]. The integration of FER with Markov modeling creates a foundation for predictive early warning systems that are capable of detecting increasing tension, signs of cognitive exhaustion, and potential risks of operator errors in real time [7].

Thus, the modern combination of computer vision, machine learning, and probabilistic modeling forms a new approach to ensuring aviation safety, in which the psycho-emotional state of personnel is considered as a measurable and predictable quantity that can significantly enhance the effectiveness of decision support systems and minimize threats associated with the human factor.

2 Methodology for Emotion Recognition and Markov Modeling of the Dynamics of Emotional States in Aviation Personnel

To assess the dynamic aspects of the human emotional sphere, seven basic emotions were selected according to Paul Ekman's classification: joy, sadness, anger, fear, surprise, disgust, and the neutral state. The use of Face Emotion Recognition technologies makes it possible to quantitatively determine, in real time, the degree to which the current facial expression belongs to each of these emotional categories.

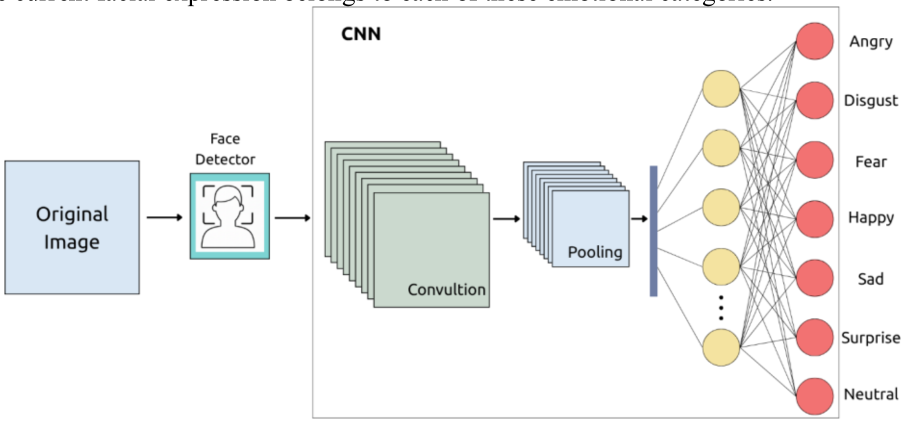

Fig. 1. Structural diagram of the emotion recognition pipeline based on a convolutional neural network (CNN)

Fig. 1 presents a detailed diagram of the emotion recognition pipeline based on a convolutional neural network (CNN). At the first stage, the input image is fed into the face detection module, which extracts the region of interest (ROI) containing the user's face. At the second stage, the selected region passes through a sequence of convolutional layers, where trained filters are used to extract local and high-level features such as eye contours, eyebrow orientations, mouth structure, and other facial expression elements. The convolution results are then reduced in spatial resolution by pooling layers, which decrease data dimensionality, reduce sensitivity to noise, and increase the model's robustness to small variations in face position. At the final stage, the resulting feature vector is passed to a fully connected classifier, which computes the probabilities that the image belongs to one of the seven emotional categories: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. Thus, the presented architecture reflects the full processing cycle—from the original image to the model's final decision.

To analyze the temporal evolution of the emotional states of aviation personnel, a stochastic model was developed based on a discrete first-order Markov chain. The model receives as input the data from the intelligent emotion recognition system, which estimates the current state of the operator according to one of seven emotion classes.

To correctly construct the time series of emotional states, two different time intervals are used: τ — a discretization interval of 1 second. At every τ seconds, the system records the current emotion e_i, on the basis of which a time series is formed:

$$E = <e_1, e_2, \ldots e_i, \ldots e_n>$$

where each element ei takes one of the integer values (1..7). To construct the transition matrix of informative events, a period T is selected — the interval for building the statistical model.

After a time series of at least T/τ observations has been accumulated, the transition matrix of the first-order Markov chain is constructed:

$$P = \begin{bmatrix} P_{11} & P_{11} & \cdots & P_{11} \\ P_{11} & P_{11} & \cdots & P_{11} \\ \vdots & \vdots & \ddots & \vdots \\ P_{11} & P_{11} & \cdots & P_{11} \end{bmatrix}$$

Each element of the matrix is computed according to the following formula:

$$P_{ij} = \frac{N_{ij}}{\sum_{k=1}^{7} N_{ik}}$$

where:

N_{ij} is the number of observed transitions from emotion i to emotion j in the sequence E; the denominator is the total number of all transitions from state i

Thus, the elements of P are interpreted as the probabilities of a change of emotional state over a single discretization step of length τ.

3 Information-analytical metrics extracted from the transition matrix of emotional states of aviation personnel

The analysis of the transition matrix and the derived characteristics of the Markov chain provides extensive opportunities for a detailed and quantitatively grounded study of the emotional dynamics of aviation personnel. In contrast to static assessment methods, the Markov approach makes it possible to treat emotions as a temporal process governed by probabilistic laws. This, in turn, enables not only the recording of current states, but also the prediction of the further evolution of emotional reactions, the identification of latent regularities, and the determination of factors influencing operator stability, as confirmed by a number of recent studies on emotion modeling based on Markov and hidden Markov models in tasks of behavior prediction, physiological signal analysis, and brain activity monitoring [8].

One of the key outcomes is the analysis of transition probabilities between emotions. The transition matrix makes it possible to determine how frequently one emotion is replaced by another, which emotional states play the role of triggers and which act as consequences. For example, if the probability of a transition from a neutral state to a state of anger or fear is significantly increased, this indicates a high susceptibility of the operator to stress factors. Such transition probabilities are actively used in intention and behavior prediction models for drivers and operators, where emotions are treated as hidden or observable states of a Markov process [9]. The analysis of these transitions makes it possible to identify potential causes of emotional instability and to determine which external influences have the most significant impact on the psychological state.

Equally important is the study of self-transitions, represented on the diagonal of the matrix. High values of the diagonal elements indicate the stability of an emotion, that is, the operator's ability to maintain a certain emotional state over an extended period of time. Low values, on the contrary, indicate a tendency toward frequent emotional fluctuations, which may suggest increased sensitivity to workload or reduced psychophysiological resilience. Such measures of state "dwell time" and self-transition probabilities are used in the analysis of emotion and cognitive state dynamics in models based on hidden Markov processes [10, 11]. These data make it possible to rank operators by their level of emotional stability and to identify personnel who require additional attention.

Particular value is provided by the long-term (stationary) distribution computed on the basis of the transition matrix.

$$\pi P = \pi, \sum_i \pi_i = 1$$

It shows what percentage of time the operator will spend in each emotional state during prolonged work. The stationary distribution reflects the person's baseline emotional background, which does not depend on short-term fluctuations or random influences. For example, if the stationary distribution indicates a high proportion of sadness, fear, or anger, this may be evidence of chronic emotional tension affecting performance and safety.

Of particular value is the long-term (stationary) distribution computed on the basis of the transition matrix. It shows what proportion of time the operator will spend in each emotional state during prolonged operation. The stationary distribution reflects the individual's baseline emotional background, which is not affected by short-term fluctuations or random perturbations. For example, if the stationary distribution indicates a high share of sadness, fear, or anger, this may be evidence of chronic emotional tension that affects performance and safety. Similar approaches are used to analyze stable behavioral patterns and emotional states in transportation and cognitive tasks [12].

For deeper analysis, multi-step probabilities are computed, making it possible to assess the likelihood of particular emotions arising after several time intervals. Such forecasts are especially important for modeling long-duration flights or shifts, under which the psychophysiological state may gradually deteriorate. Multi-step matrices enable the advance prediction of the probability of transitions to stress-related emotions and the timely implementation of measures to prevent the onset of critical states, in a manner analogous to the way multi-step Markov models are employed to forecast the evolution of intentions and the risk of hazardous behavior in drivers and crew members.

Another important indicator is the expected time to transition into stress states. It is calculated on the basis of the fundamental matrix and reflects how long an operator is able to maintain a calm or neutral state before a stress reaction occurs. Such characteristics of the mean time to the onset of an adverse state are used in assessing the safety and reliability of crew and operator behavior in aviation and transport. This type of analysis has practical value for planning shift durations, distributing workload, and assessing the risk of errors associated with fatigue.

Finally, an important metric is the entropy of the transition matrix, which characterizes the degree of uncertainty in emotional behavior. High entropy indicates that transitions between emotions are chaotic and unpredictable, which may suggest a high level of emotional tension or instability. Low entropy, on the contrary, points to orderliness and stability of emotional reactions. In a number of studies on the analysis of emotion dynamics and brain activity, entropy-based and information-theoretic measures are used for the quantitative assessment of the complexity and variability of emotional transitions in Markov and hidden Markov models [4, 6–8]. Taken together, all these metrics form a comprehensive picture of emotional dynamics, enabling not only the recording of the current state but also the prediction of its evolution, the identification of risks, and the development of measures to reduce the impact of the human factor on flight safety. This approach makes the Markov model a powerful tool for analyzing the psychophysiological state of aviation personnel and for optimizing real-time monitoring systems.

4 Results

Based on the operation of the intelligent Face Emotion Recognition system, time series of probabilities for seven emotional states (Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral) were obtained for aviation personnel under simulated operational scenarios. Each series represented a sequence of probability vectors recorded with a discretization step of $\tau = 1$ s, which provided sufficiently high temporal resolution for analyzing rapid changes in facial expressions and emotional reactions. Fig. 2 presents an example of a single video frame with the classification result: above the facial region, the most likely emotion (in this case, Neutral) and its corresponding probability value are displayed.

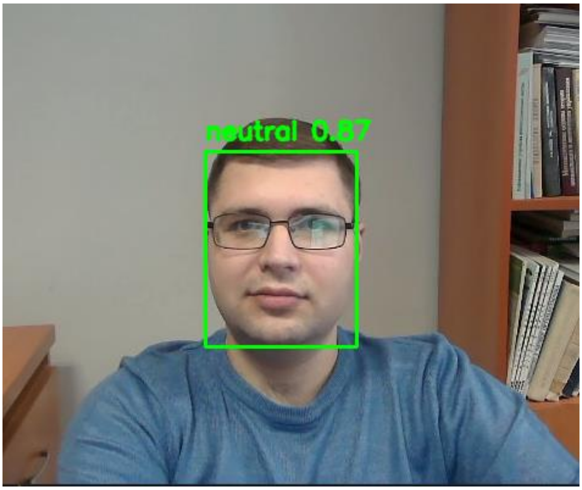

Fig. 2. Example video frame with the output of the emotion recognition system

A fragment of a typical model output for the first seconds of observation is presented in Table 1. It can be seen that, already in the initial segment of the time series, the neutral state (Neutral) dominates with a probability on the order of 0.8–0.9, while the values of negative emotions (Angry, Fear, Sad) lie in the range of 0.0–0.1. The positive emotion Happy appears periodically with moderate intensity (up to 0.20–0.23), which corresponds to a relatively calm yet engaged state of the operator in the baseline experimental mode.

Table 1. Fragment of the time series of emotional state probabilities generated by the Face Emotion Recognition module

Time (s)	Angry	Disgust	Fear	Happy	Sad	Surprise	Neutral
0.00	0.02	0.00	0.01	0.10	0.02	0.01	0.84
0.21	0.04	0.00	0.01	0.06	0.02	0.00	0.87
0.41	0.14	0.00	0.02	0.04	0.05	0.02	0.73
0.63	0.29	0.00	0.15	0.04	0.10	0.02	0.39
0.84	0.10	0.00	0.12	0.02	0.23	0.01	0.52
1.05	0.13	0.00	0.11	0.02	0.10	0.01	0.63
1.27	0.20	0.00	0.06	0.06	0.12	0.00	0.56
1.47	0.07	0.00	0.01	0.02	0.07	0.00	0.83
1.68	0.03	0.00	0.00	0.01	0.03	0.00	0.93
1.90	0.04	0.00	0.01	0.04	0.10	0.02	0.80
2.12	0.38	0.00	0.03	0.06	0.16	0.03	0.34
2.32	0.05	0.00	0.01	0.05	0.12	0.00	0.76
2.66	0.03	0.00	0.08	0.03	0.22	0.00	0.64

Based on the obtained time series, for each operator and for each operating mode (baseline, increased workload, fatigue), discrete sequences of dominant emotions were formed, which were then used to construct first-order Markov chain transition matrices. The structure of the set of states and the possible transitions between them is schematically shown in Fig. 3.

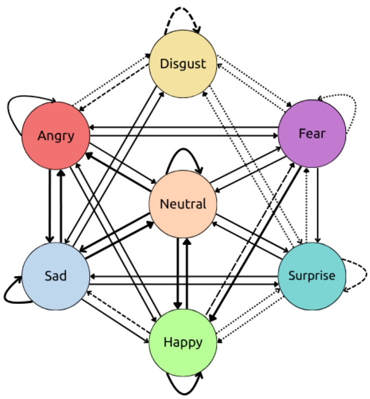

Fig. 3. State-transition diagram of the discrete Markov chain for the seven emotional states of aviation personnel

Over a longer time interval, the dynamics of emotion probabilities were analyzed, and the corresponding plots of their variation were constructed (Fig. 4). The diagram covers approximately 60 s of observation and shows that, on average, the neutral state remains dominant; however, at certain moments bursts of both positive (Happy, Surprise) and negative emotions (Angry, Sad, Fear) are recorded. Most of these bursts are short-lived and rapidly decay, which indicates the operator's ability to return to a neutral emotional baseline after external or internal perturbations.

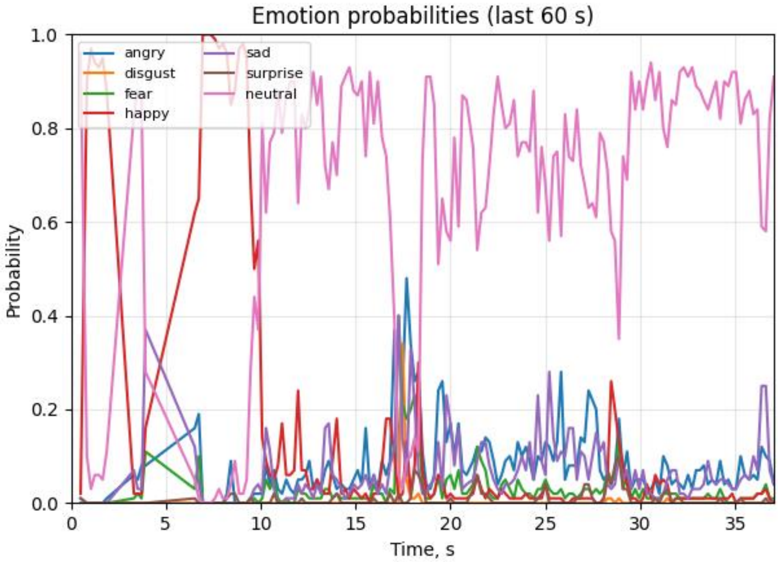

Fig. 4. Dynamics of the probabilities of seven emotional states of aviation personnel over 40 s of observation

The obtained results demonstrate that the integration of Face Emotion Recognition technologies with Markov analysis provides not only the registration of instantaneous emotional reactions, but also their formalized quantitative description over time. This approach makes it possible to identify individual features of emotional resilience, track the probabilistic dynamics of transitions between states, and predict the risk of shifts toward unfavorable psychophysiological regimes that are critically important for ensuring aviation safety.

5 Conclusions

The results obtained confirm that the integration of Face Emotion Recognition technologies with Markov analysis is an effective tool for investigating the dynamics of the psycho-emotional state of aviation personnel. This approach ensures not only the recording of current emotional reactions, but also their quantitative description over time, making it possible to identify characteristic transition patterns, the degree of stability of emotional states, and individual features of emotional regulation.

Markov models have shown that the emotional behavior of an operator possesses a probabilistic structure, and that stationary distributions reflect the tendency toward the formation of a long-term emotional background, which is important for the early detection of signs of chronic tension. Predictive characteristics of Markov chains, such as the expected time to the onset of stress states, make it possible to establish foundations for early warning systems aimed at detecting a decline in operator resilience.

Thus, the combination of FER and Markov analysis creates a scientifically grounded platform for the development of intelligent simulators and monitoring systems, in which emotional parameters are treated as measurable and predictable. This increases the accuracy of human-factor assessment and contributes to the prevention of adverse psychophysiological states that are critical for aviation safety.

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