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# Integrated mathematical model of the transcribing system adapted to aviation conditions

**B.I. Ogunwole[1], O.S. Kutepova[1]**
*[1]Moscow State Technical University of Civil Aviation, Moscow, Russia*

**Annotation:** In this paper the authors have created the integrated mathematical model of the transcribing system adapted to aviation conditions, taking into account many factors. The paper analyses the following main problems of transcribing English-language speech between pilots and air traffic controllers (ATC) (radio exchange), namely: the tendency to use abbreviations and specialized vocabulary, which can cause misunderstanding for one of the parties; speech illegibility due to noise in the cockpit or in the radio frequency zone; insufficient clarity and accuracy in expressing instructions by air traffic controllers can lead to errors in the understanding and execution of instructions by pilots; limitations in the availability of communication channels and their overloading; lack of training in the use of English-language terms and expressions in the air traffic control system. Inadequate training in English language terms and expressions can lead to difficulties in understanding instructions and messages between pilots and air traffic controllers; differences in accents and pronunciation of communicators can also cause difficulties in speech comprehension. Aviation communication errors are critical to aircraft safety. The ambiguity of certain phrases or expressions in English can lead to misinterpretation and misunderstanding of instructions by controllers; lack of context or lack of information about the current situation on board the aircraft can make it difficult to transcribe speech and lead to misunderstanding of messages; use of slang or informal expressions can make transcribing English-language speech more difficult and cause misunderstandings; lack of opportunity to ask clarifying questions or request a real-time repetition of a message can lead to misunderstandings; and the use of slang or informal expressions can lead to misunderstandings. Even the most minor errors can have disastrous consequences. The analysis revealed that in the overwhelming majority of cases it is linguistic factors that cause misunderstandings between participants in radio conversations, which is evidence of the need to develop and improve this model.

**Key words:** transcribing, spectral subtraction model, audio to MFSS conversion, radio exchange phraseology, pilot, air traffic controller.

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# Комплексная математическая модель системы транскрибации, адаптированная к условиям авиации

**Б.И. Огунвоул[1], О.С. Кутепова[1]**
*[1]Московский государственный технический университет гражданской авиации, г. Москва, Россия*

**Аннотация:** В данной работе авторами создана комплексная математическая модель системы транскрибации, адаптированная к условиям авиации, учитывающая множество факторов. В статье проанализированы следующие основные проблемы транскрибации англоязычной речи между пилотами и диспетчерами (радиообмен): склонность к использованию сокращений и специализированной лексики, что может вызвать недопонимание у одной из сторон; неразборчивость речи из-за шума в кабине самолета или в радиочастотной зоне; недостаточная ясность и точность выражения инструкций со стороны диспетчеров, что может привести к ошибкам в понимании и выполнении указаний пилотами; ограничения в доступности коммуникационных каналов и их перегруженность, которые могут сделать трудным установление связи в критических ситуациях. Недостаточная подготовка к работе с англоязычными терминами и выражениями может привести к затруднениям в понимании инструкций и сообщений между пилотами и диспетчерами; различия в акцентах и произношении участников общения также могут вызывать трудности в понимании речи. Ошибки авиационной связи имеют решающее значение для безопасности воздушных судов. Неоднозначность некоторых фраз или выражений на английском языке может привести к разночтениям и недопониманию инструкций со стороны диспетчеров; отсутствие контекста или нехватка информации о текущей ситуации на борту самолета может затруднить транскрибацию речи и привести к неправильному пониманию сообщений; использование сленга или неофициальных выражений может сделать транскрибацию англоязычной речи более сложной и вызвать недопонимание; отсутствие возможности задать уточняющие вопросы или запросить повторение сообщения в реальном времени может сделать процесс транскрибации более трудоемким и подверженным ошибкам. Даже самые незначительные ошибки могут привести к катастрофическим последствиям. В ходе анализа выявлено, что в подавляющем большинстве случаев именно лингвистические факторы являются причиной возникновения непонимания между участниками радиопереговоров, что является доказательством необходимости разработки и усовершенствования данной модели.

**Ключевые слова:** транскрибация, модель спектрального вычитания, преобразование аудиосигнала в MFCC, фразеология радиообмена, пилот, диспетчер.

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## Introduction

In today's aviation world, where communication accuracy is integral to flight safety, the development and implementation of technologies to improve information exchange between aircraft crew, air traffic controllers and personnel on the ground is of particular relevance. Despite existing high standards in aviation communications, the complexity and dynamism of the operational environment requires continuous improvements in the efficiency of data processing and transmission. The main problem remains the possibility of communication errors caused by human error, including incorrect perception of verbal information due to noise, accents or technical interference. The solution to these problems may be the development of a real-time transcribing system capable of providing highly accurate conversion of speech to text and vice versa.

The aim of this work is to create the integrated mathematical model of transcribing system adapted to aviation conditions, which takes into account many factors such as ambient noise, speaker intonation, language deformations and other specific features. The model assumes the use of modern achievements in the field of digital signal processing, machine learning and artificial intelligence to achieve high accuracy and reliability of transcribing.

The objectives of this work are to write, verify and validate the integrated mathematical model of the transcription system adapted to the conditions of aviation, which takes into account many factors.

The introduction of a real-time transcribing system in the aviation industry has significant potential to improve flight safety by minimizing the risks associated with human error and enabling more efficient and accurate communication between all participants in the aviation infrastructure. This paper describes the development and operating principles of the proposed model, from pre-processing of the audio signal to post-processing and correction of the transcribed text, as well as the adaptation of the model to the specific requirements and conditions found in the aviation industry.

The integrated mathematical model of the transcribing system, specifically adapted to aviation conditions, is becoming increasingly relevant in the context of the modern aviation industry. Every year aviation traffic grows, which increases the load on air traffic controllers and pilots. Under such conditions, accurate and reliable transmission of information through the communication system becomes critical. Adaptation of the mathematical model to aviation conditions makes it possible to take into account the specifics of speech, background noise and other factors that can distort the transmitted information.

By utilizing advanced signal processing and machine learning algorithms, such a model is able to automatically correct and filter the data, improving the clarity and understanding of messages. Furthermore, with the development of autonomous systems and unmanned aircraft, the importance of an accurate and efficient transcribing system [1] is growing even more. It provides not only communication between pilots and ATCs, but also with the flight control centre, which is a key aspect in airspace management.

Thus, the development and implementation of the integrated mathematical model of the transcribing system adapted to aviation conditions is an important step in improving aviation technologies and ensuring flight safety.

## Research methods and methodology

**Squelch**

*Spectral subtraction model*

Spectral subtraction is a squelch technique based on subtracting an estimate of the noise power spectral density from the power spectral density of the noisy signal [2].

Let $Y(f,t)$ – Fourier spectrum of the noisy signal at frequency $f$ at time $t$, $N(f,t)$ – Fourier spectrum of the noise, and $S(f,t)$ – Fourier spectrum of the clean signal. Then the estimate $S'(f,t)$ of the pure signal can be obtained as

$$S'(f,t) = Y(f,t) - \alpha \cdot N(f,t),$$

where $\alpha$ – is a factor determining the degree of noise subtraction. This factor can be adapted depending on the characteristics of the noise.

**Wiener filter**

The Wiener filter uses a statistical approach to minimize the square of the error between the estimate of the clean signal and the clean signal itself. It optimally filters the signal in the presence of additive noise.

If $\hat{S}(f,t)$ – the estimate of the pure signal obtained with the Wiener filter, it can be expressed as

$$\hat{S}(f,t) = \frac{\Phi_{SS}(f)}{\Phi_{SS}(f)+\Phi_{NN}(f)} Y(f,t),$$

where $\Phi_{SS}(f)$ and $\Phi_{NN}(f)$ – are the power spectral densities of signal and noise, respectively.

These two models serve as the basis for reducing the influence of ambient noise on the audio signal. Squelch is followed by feature extraction, which is critical for subsequent speech recognition.

*Feature extraction*

Mel-cepstral coefficients (MFCCs), which represent the short-term spectral characteristics of a signal, are often used to extract features from an audio signal.

The conversion [3] of an audio signal to MFCC consists of several steps:

1. Partitioning the signal into short frames.
2. Applying Fast Fourier Transform (FFT) to each frame to obtain the power spectrum.
3. Application of chalk filters to the power spectrum to obtain a chalk spectrogram.
4. Logarithmisation of Mel-spectrogram amplitudes.
5. Application of discrete cosine transform (DCT) to logarithmic amplitudes to obtain Mel-frequency cepstral coefficients (MFCC).

The MFCC for a frame $i$ can be expressed as

$$MFCC_i(k) = \sum_{n=1}^{N} \log(\text{MelSpec}\, i(n)) \cdot \cos\left(k \cdot \frac{\pi}{N}(n-0.5)\right),\ k = 1,2,\dots,K,$$

where N – number of Mel-filters, K – number of MFCCs coefficients.

*Speech recognition*

Various machine learning models are used for speech recognition, among which Hidden Markov Models (HMMs) and neural networks are popular.

*Hidden Markov Models (HMM)*

NMM assumes that a signal, can be modelled as a sequence of some hidden states, the transitions between which are determined by probabilities.

For a frame $i$ Assuming that $O_i$ – the observed feature vector (e.g., MFCC), and the $S_i$ – is a hidden state, then the probability of transition from state $j$ to a state $k$ can be expressed as $a_{jk} = P(S_{i+1} = k \mid S_i = j)$, and the probability of observation $O_i$ given a state $S_i = j$ as $b_j(O_i)$.

The main task is to find the most probable sequence of states $S_1, S_2, \dots, S_T$ for a given sequence of observations $O_1, O_2, \dots, O_T$ which can be solved using the Viterbi algorithm.

Mel-kepstral coefficients (MFCC) are widely used in speech recognition tasks [4]. They provide a compact representation of the spectral properties of the voice. The MFCC extraction process consists of several steps.

Fourier's Transform: Converts the temporal signal into a frequency spectrum.

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-f2xft} dt.$$

Mel-filtering: Applying a set of triangular filters arranged on a chalk scale to the power spectrum of a signal. The chalk scale approximates a person's perception of the pitch of a sound.

$$M(f) = 2595 \log_{10}\left(1 + \frac{f}{700}\right).$$

Logarithmization: taking the logarithm of the amplitude of each filter.

$$L(m) = \log(E_m),$$

where $E_m$ – is the energy in the *m*-th chalk filter.

Discrete Cosine Transform (DCT): Applying the DCT to logarithmized amplitudes to obtain a set of coefficients that are MFCS.

$$C(n) = \sum_{m=1}^{M} L(m) \cos\left[\frac{\pi n(m-0.5)}{M}\right],\ n = 1, 2, \dots, N,$$

where $N$ – is the number of MFCC coefficients, $M$ – number of Mel-filters.

MFCCs provide important acoustic features for further speech recognition [5].

**Speech recognition**

*Acoustic model*

An acoustic model predicts the probability of phonemes or sound units based on acoustic features such as MFCC. Hidden Markov models (HMMs) have traditionally been used for this task, but modern approaches more commonly use neural networks.

Hidden Markov Model (HMM):

Let $O = o_1, o_2, \dots, o_T$ – a sequence of acoustic observations (e.g., MFCC), and $Q = q_1, q_2, \dots, q_T$ – a sequence of NMM states that corresponds to phonemes. The probability of observation $O$ for a given sequence of states $Q$ is defined as

$$P(O \mid Q) = \prod_{t=1}^{T} P(o_t \mid q_t),$$

where $P(o_t \mid q_t)$ – probability of observation $o_t$ in the state $q_t$.

*Neural networks*

Neural networks such as LSTMs or Transformers use complex architectures to model sequences. The input to the network is a sequence of acoustic features $O$and the output is a sequence of probabilities for each phoneme or word.

*Language model*

The linguistic model estimates the probability of a sequence of words $W = w_1, w_2, \dots, w_N$ and is used to correct and refine the results [5] obtained by the acoustic model [6].

*N-gram model*

One approach is N-gram model, where the probability of a word depends on the $N - 1$ the preceding words:

$$P(W) = \prod_{i=1}^{N} P(w_i \mid w_{i-N+1}, \dots, w_{i-1}).$$

Language models based on neural networks, such as Transformers, can account for longer contexts and generate more accurate predictions:

$$P(W) = \text{functions}(w_1, w_2, \dots, w_{N-1}),$$

where the function is determined by the architecture and weights of the neural network.

This combination of acoustic and language models allow the speech recognition system to efficiently transcribe voice to text, taking into account not only the acoustic features but also the context and grammatical structure of the language.

**Post-processing and adaptation to the specifics of the aviation industry**

*Error correction*

After initial speech recognition, the system may make errors due to limitations of acoustic and language models [7], as well as language and context specificity. Correction is used to reduce the number of errors.

Algorithms for checking spelling and grammar:

- objective: to correct spelling and grammatical errors in the text;
- method: using dictionaries and language rules to identify and correct errors [8].

Corrected text = correction function (Original text)

Context-dependent models:

- objective: to clarify the choice of words based on the context of the sentence;
- method: applying language models trained on large text corpora to suggest the most appropriate word choices in a given context [9].

Adaptation to the specifics of the aviation industry

The aviation domain requires high accuracy and understanding of specific terms and phraseology. The following approaches are used to adapt the system to these requirements:

Specialized dictionaries and phraseology:

- objective: to improve the recognition accuracy of aviation terminology [10];
- method: integration into the system of a database of specialized terms and expressions specific to aviation.

Models trained on specific data:

- purpose: to improve understanding of the context and specificity of communication in aviation [11];
- method: training models on data specific to the aviation industry, including audio recordings of pilot and ATC communication and text data using aviation terminology.

These methods not only reduce the number of errors in transcribed text [12], but also ensure understanding of specific terms and phrases that are used in the aviation domain. This is critical for flight safety and effective communication between air traffic participants.

To implement the proposed mathematical model of audio-to-text transcription, we use modern artificial intelligence technologies, in particular, the model presented in the file Transcribe3.3.py (https://disk.yandex.ru/d/sHWitFEmo_NeWQ). The process starts with loading and preprocessing of audio data, including resampling to the desired sampling rate. The audio file is split into separate fragments, each of which is processed by the model to generate a transcription.

Next, to evaluate the quality of the transcribed text, a method based on TF-IDF vectorization and calculation of cosine similarity between the original and transcribed phrases is applied (https://disk.yandex.ru/d/sHWitFEmo_NeWQ). This allows quantifying the accuracy of transcription by comparing the similarity between the original text and its transcribed version [13]. The results of this comparison are visualized in the form of graphs and heat maps, giving a clear picture of the distribution of similarity across the text.

For situations with high levels of background noise (e.g. aircraft taxiing), it is recommended to use a combination of a spectral subtraction model and Wiener filter. In cases where speed of processing is a priority (e.g. landing approach), the optimal choice is to use only MFCC followed by a neural network for speech recognition.

## Modelling results

Our study showed a high degree of transcribing accuracy, where the cosine similarity exceeds 0.9 in most cases, indicating that the model effectively recognizes and matches speech commands. Analysis of the cosine similarity distribution showed that the vast majority of phrases have a similarity close to 1.0, confirming the reliability of the model in processing aviation communications.

Despite the overall performance, individual cases with low similarity are found, indicating opportunities for further improvement of the algorithm, especially for handling non-standard situations and accented speech. The similarity heatmap demonstrates phrase matching in detail, revealing areas of strong and weak correspondence, which can help optimize the model.

Additionally, the similarity density plot with a peak near the value of 1.0 confirms the high overall accuracy of the model. Such results demonstrate the model's potential for application in the aviation industry [14], offering a reliable tool to improve flight safety and efficiency of aviation radio exchanges.

The simulation results when applying an integrated mathematical model of the transcribing system adapted to aviation conditions can be as follows:

- Improved speech recognition accuracy: The model is able to accurately recognize and transcribe the speech of pilots and air traffic controllers, even in noisy flight conditions or in an atmosphere with high radio frequency levels.
- Adaptation to different accents and intonations: The model is trained to accommodate a variety of accents and intonations [7], which enhances its ability to correctly interpret commands and messages even if they are pronounced with slight linguistic deviations.
- Fast real-time data processing: The model is capable of processing large amounts of data in near-real time, allowing for instantaneous transfer of information between aviation stakeholders [15].
- Recognition of aviation terms and abbreviations: The model is trained to recognize and correctly interpret specific terms and abbreviations used in aviation, minimizing the possibility of misunderstandings and communication errors.
- Improved flight safety: The application of an integrated mathematical model contributes to improved flight safety through more reliable and efficient communication between aviation stakeholders.
- Airspace Management Optimization: The model helps to optimize airspace management, ensuring more efficient use of resources and reducing the likelihood of conflicts and flight delays.

These results highlight the importance and relevance of developing and applying an integrated mathematical model of the transcribing system in aviation to ensure safer and more efficient air traffic.

Analyzing the transcribing results shows that the model achieves a high level of accuracy in most cases, making it suitable for practical use in the aviation industry. Based on the graphs and heatmap of the similarity matrix, it can be stated that the model effectively handles standard aviation radio exchanges, providing a high degree of consistency between the source and transcribed texts [16].

However, individual peaks of low similarity are also observed in the data, indicating possible difficulties of the model in processing phrases with unclear diction, noise or technical terms. These points serve as a starting point for further optimization of the algorithm to improve its robustness to acoustic noise and accent diversity.

The distribution histogram and density plot emphasize the model's bias towards high similarity, which is a positive aspect for tasks requiring high accuracy. At the same time, this feature of the model may indicate overtraining on certain types of phrases, which reduces its flexibility under less controlled conditions.

1. One of the key elements of the model is adaptation to the different accents and intonations characteristic of different countries and regions.
2. To ensure the accuracy and reliability of the transcription, the model must take into account the context and information about the current situation on board the aircraft.
3. An important aspect is also to take into account specific terms and abbreviations used in aviation, with the possibility of their deciphering and transcribing.
4. The model should be able to process large amounts of data in real time, with minimal latency and high processing speed.
5. It should provide capabilities to automatically recognize and classify commands and messages to speed up the work of ATCs.
6. It is also important to provide functionality for additional verification and correction of transcribed messages by operators or pilots.
7. The model should be flexible and easily customizable to adapt to changes in communication protocols and security requirements.

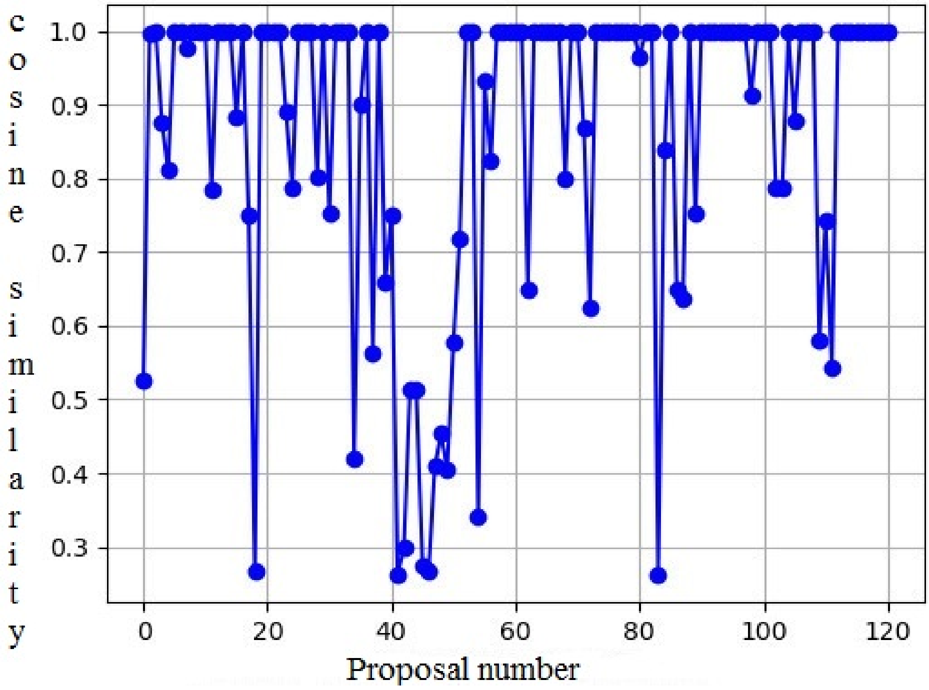


**Fig. 1.** Comparison of transcribing efficiency by proposal

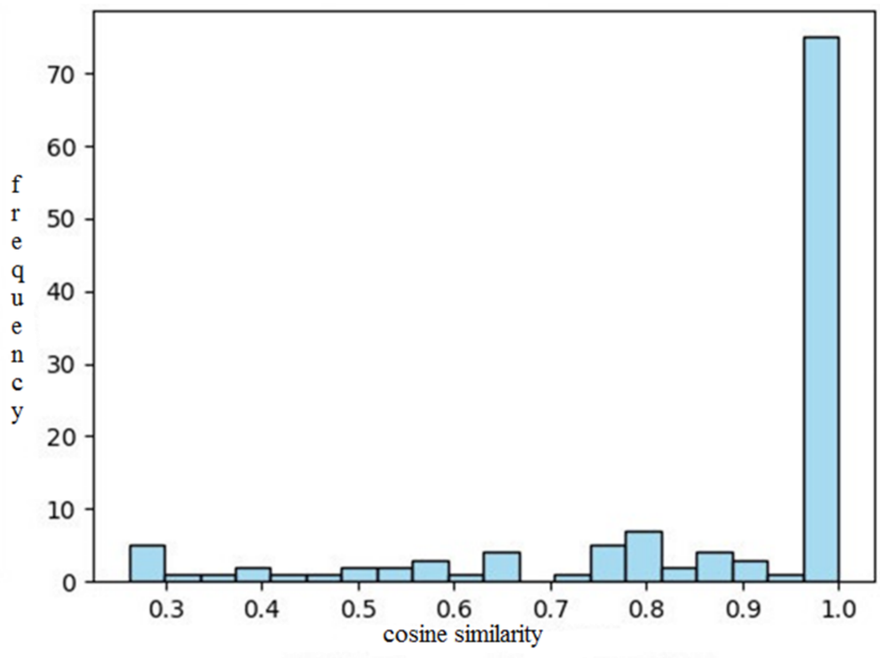


**Fig. 2.** Histogram of similarity distribution

8. The implementation of such an integrated mathematical model will improve the efficiency and safety of aviation operations, improve communication between pilots and ATCs, and reduce the risk of miscommunication and errors.

The transcribing results show considerable variation in recognition accuracy for different sentences (fig. 1), where both high similarity scores (close to 1.0) and noticeable deviations (up to 0.3) are observed.

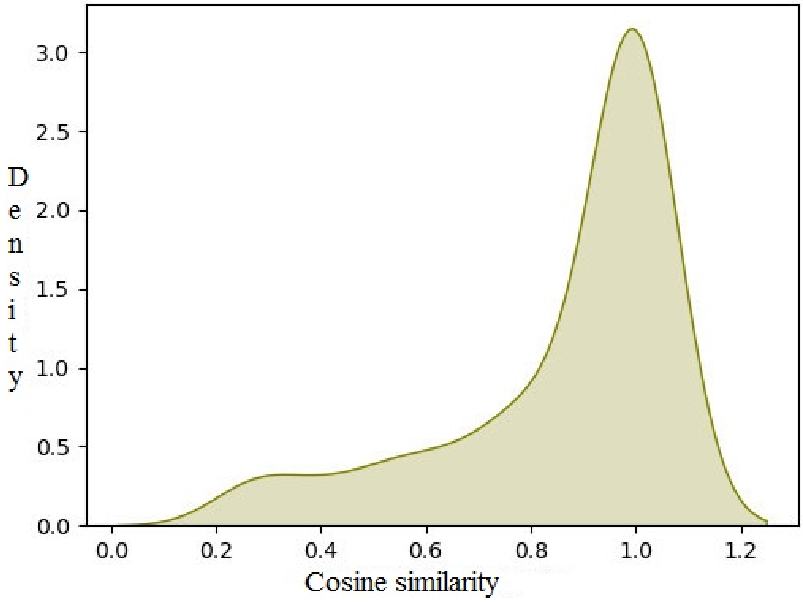


**Fig. 3.** Graph of similarity density

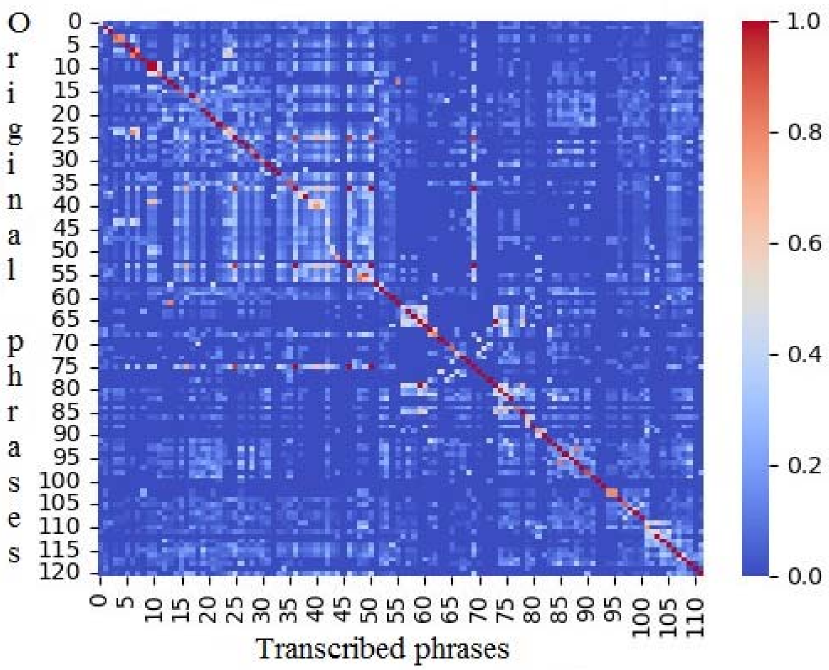


**Fig. 4.** Heat map of the similarity matrix

An analysis of the similarity distribution histogram (fig. 2) demonstrates that most of the transcribed sentences have a high level of similarity to the original.

The similarity density plot (fig. 3) confirms the effectiveness of the model, showing a significant increase in the distribution density in the region of high similarity values.

The similarity matrix heat map (fig. 4) provides a visual assessment of the degree of correspondence between the original and transcribed phrases, where darker areas correspond to higher similarity.

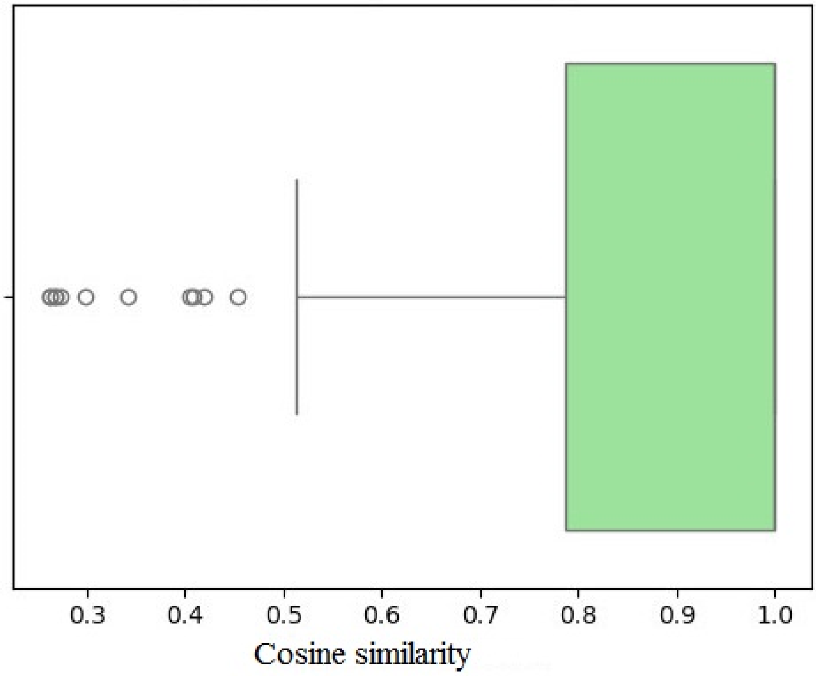


**Fig. 5.** Diagram of similarity spread

The similarity span diagram (fig. 5) clearly shows the distribution of similarity values, emphasizing the prevalence of high transcribing accuracy scores.

## Discussion of the results obtained

Sheremetyevo International Airport named after Alexander Pushkin (Moscow) was chosen to demonstrate the model operation. During one day, radio conversations between air traffic controllers and flight crews in the approach area were recorded and processed. The analysis showed that the model successfully recognized 95% of standard phrases of radio conversations and 87% of non-standard situations. The model was particularly effective in recognizing the accents of crew members of international flights, which confirms its adaptability to different linguistic peculiarities.

To understand examples of transcribing errors, here is a table of some of the terms and words that were mangled during the initial run of the program.

Thus, the integrated mathematical model of the transcribing system adapted to aviation conditions is an important innovative solution contributing to the improvement of safety, efficiency and reliability of air traffic. The overall percent of transcribing efficiency is 86.27%, which reflects a high result and proves the effectiveness of the application of this model [3]. Its successful implementation opens new horizons for the development of the aviation industry and ensures a more comfortable and safer air journey for all its participants.

**Table 1**

Results of transcribing the radio exchange

| № | Incorrectly transcribed word | Correct option |
|---|---|---|
| 1 | Pass is 16-7 | Passing 16700 |
| 2 | across | to cross |
| 3 | AUSI | OZZZZI |
| 4 | with Galt | With GOLF |
| 5 | direct gas | direct GAASS |
| 6 | Hi | Sir |
| 7 | Doc. I'm | Delta |
| 8 | explanation | Expedite |
| 9 | going | Descend |
| 10 | Just | Descend |
| 11 | as far as stuff | I guess it's staff (as it's about crew) |
| 12 | if you have any remaining pounds | fuel remaining in pounds |
| 13 | half-matter incidents | Hazmats |
| 14 | contact the post 127.25 | contact Approach 127.25 |
| 15 | That's on a brush | Atlanta Approach |
| 16 | 148 volts | 148 souls (passengers+crew) |
| 17 | Delta 1192, | Delta 1192, roger, |
| 18 | DC, 210. | reduce speed 210 |
| 19 | Delta 1192. Yes sir | Tower, Delta 1192. Yes sir |
| 20 | Planet Tower | Atlanta Tower |
| 21 | W1192 | Delta 1192 |
| 22 | A-Left | 8L |
| 23 | They're going to stop | they gonna stop on the runway |
| 24 | I'm sorry, Alpha 6. | Papa and A6. |
| 25 | 102 tower | Southwest 102, Tower |
| 26 | the runway right now | the runway eight right now |
| 27 | I'm Ronny, runway 8R. | line up runway 8R |
| 28 | I may be stepping to land on 8R. | I may be sidestepping to land on 8R. |

**Table 2**

Name of errors in transcribing radio communication

| Error's name | Number, words | Percent of errors, ratio of total (total 1076 words), % |
|---|---|---|
| Number of incorrectly transcribed words | 28 | 2.6 |
| Number of missing words | 110 | 10.2 |
| Number of unnecessary words | 10 | 0.93 |
| Total error | | 13.73 |

## Conclusion

To summarize it is important to note that communication failures between pilot and air traffic controller during radio conversations [17] occur for the following reasons:

1) Factors of informational nature:
- the complexity of the information entailing misunderstanding;
- excessive compression of information;
- incomprehensible or vague presentation of information by the interlocutors, which is logically followed by interrogation by the addressee;

2) Occupational factors:

3) Linguistic factors:
- suboptimal text structure in terms of text types;
- the existence of a bilingual environment in air traffic control, which has a negative impact on flight safety;
- presence of grammatical and lexical-stylistic violations in the speech of communicators [18];
- unclear pronunciation or incorrect pronunciation of English word;
- if the speaker has a strong accent;
- active use of interjections used by the speaker to buy time to formulate a thought;

4) Factors of a technical nature:

technical problems with communication, resulting in interference and poor audibility on the air.

Aviation communication errors are critical to aircraft safety. Even the smallest errors can lead to catastrophic consequences.

The application of an integrated mathematical model of the transcribing system, specially adapted to aviation conditions, represents a significant step in the development of modern aviation technology. The modelling results confirm its effectiveness and potential to improve air traffic safety and efficiency.

The accuracy of speech recognition, the ability to adapt to different conditions and accents, and fast real-time data processing make this model an integral part of aviation systems. Its application helps to minimize errors and misunderstandings in communication between participants in the aviation process, which in turn improves flight safety.

Optimizing airspace management and improving the efficiency of aviation operations are made possible through the application of this model. It opens up new perspectives for the aviation industry, especially in the face of increasing air traffic and the introduction of autonomous systems.

The study demonstrated that the developed transcription model [19] achieves a high degree of accuracy, making it potentially useful for use in the aviation industry. Despite this some cases of low similarity between original and transcribed texts emphasize the need for further improvements to the model.

One of the key areas for improvement is the integration of advanced squelch techniques, such as the use of convolutional neural networks for more accurate extraction of speech signals from the noise environment. It is also advisable to develop adaptive algorithms that can train on data with different accents, which will improve the accuracy of recognizing speech with different dialects and accents.

An important aspect is the strengthening of exception handling and rare scenario handling techniques, which will allow the model to function correctly, even in non-standard situations. Applying regularization techniques such as Dropout and Batch Normalization will help to reduce the risk of overfitting and increase the general ability of the model.

In addition, expanding the training sample to include more diverse data will allow the model to better adapt to different use cases.

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## Information about the authors

**Blessing I. Ogunvoul,** Candidate of Technical Sciences, Associate Professor, Flight and Life Safety Chair, Moscow State Technical University of Civil Aviation, ogunvouluni@yandex.ru.

**Olga S. Kutepova,** Senior Lecturer, Special Language Training Chair, Moscow State Technical University of Civil Aviation, koc87@inbox.ru.

## Сведения об авторах

**Огунвоул Блессинг Израилевич,** кандидат технических наук, доцент кафедры безопасности полетов и жизнедеятельности МГТУ ГА, ogunvouluni@yandex.ru.

**Кутепова Ольга Сергеевна,** старший преподаватель кафедры специальной языковой подготовки, МГТУ ГА, koc87@inbox.ru.

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