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E-Pilots : A System to Predict Hard Landing During the Approach Phase of Commercial Flights

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ABSTRACT

Flight safety is a hot topic in the aviation industry. Statistics show that safety incidents during landing are closely related to the flare phase because this critical period requires extensive pilot operations. Many airlines require that pilots should avoid performing any forward stick inputs during the flare. However, our statistical results from about 86,504 flights show that this unsafe pilot operation occasionally happens. Although several case studies were conducted previously, systematic research, especially based on a large volume of flight data, is still missing. This paper aims to fill this gap and provide more insights into the issue of pilots' unsafe stick operations during the flare phase. Specifically, our work is based on the Quick Access Recorder (QAR) data, which consist of multivariate time-series data from various flight parameters. The raw data were carefully preprocessed, then key features were extracted based on flight expert experience, and a K-means clustering algorithm was utilized to divide the unsafe pilot operations into four categories. Based on the clustering results, we conducted an in-depth analysis to uncover the reasons for different types of unsafe pilot stick operations. In addition, extensive experiments were conducted to further investigate how these unsafe operations are correlated with different factors, including airlines, airports, and pilots. To the best of our knowledge, this is the first systematic study analyzing pilots' unsafe forward stick operations based on a large volume of flight data. The findings can be used by airlines to design more targeted pilot training programs in the future.

Keywords : Aviation Safety, Flight Data, Unsupervised Learning, Pilot Operation, QAR, K-Means Clustering.

I. INTRODUCTION

Flight safety is one of the most important topics in the aviation industry [1]. According to the 2020 EASA (European Union Aviation Safety Agency) annual safety review (EASA Annual Safety Review: 2020, https://www.easa.europa.eu/document-library/generalpublications/annual-safety-review-

2020, accessed on 22 November 2022), the final approach and landing phases are the most prone to flight safety accidents. As shown in Figure 1, during 2009–2018 and 2019, the total accidents and serious incidents rate accounted for 68 and 74%, respectively, in the approach and landing phases, even though these two phases only occupy 4% of the entire flight time. During these two phases, extensive pilot operations are required to make sure the aircraft is landing steadily, and any pilot misjudgment or inappropriate operation may lead to adverse consequences, such as flight safety incidents or accidents, especially when the weather condition is not ideal [2], or the aircraft is landing at high altitude airports [3].

In general, although the overall occurrence of serious flight safety accidents in the aviation industry is very rare, the possibility of adverse events (e.g., flight exceedances) that may affect flight safety and further lead to severe accidents cannot be ignored. For example, it is not uncommon for the vertical acceleration to be too large at the touchdown moment, which is called the hard landing incident [4,5], and this incident may cause severe damage to the landing gears. Excessive vertical overload not only gives passengers a bad flight experience but also largely increases the airlines' maintenance costs. Severe incidents may even threaten the lives of passengers. According to [6], the most important reason for the increase in the vertical overload is due to the pilot's inappropriate applying of forward stick inputs which makes the aircraft nose down before it touches the ground. This operation usually reduces the pitch angle of the aircraft, which will further reduce the lift force the aircraft can gain. If this happens in the flare phase [7], i.e., the few seconds before touchdown, then with a high probability the aircraft will touch ground with an excessive vertical overload, which causes the hard landing safety incident [8,9]. Therefore, we define the event in which a pilot performs this forward stick operation as an adverse event. Actually, from the Airbus A320 Flight Crew Techniques Manual (FCTM), a pilot should avoid applying any nose down inputs during the flare phase to avoid the hard landing or bounced landing risk. However, our statistical results from about 86,504 flights show that this unsafe pilot operation occasionally happens.

II. RELATED WORK

The research of flight safety incident prediction mainly aims to establish forecasting models which can be utilized as a warning before a safety incident occurs. For a hard landing, Cao et al. [17] and Hu et al. [8] took advantage of a BP neural network and an SVM to predict the incident, respectively. Because both of them are relatively early works, their prediction accuracy is unsatisfactory. Then, Qiao et al. [18] tried to use the RBF neural network and K-means clustering algorithm to predict a hard landing. With the rise of deep learning and in order to capture time-series features, Tong et al. [9] proposed a model based on the Long Short-Term Memory (LSTM) network to predict a hard landing. The same model was also used to address the landing speed prediction problem [19] and the tail strike risk prediction problem [20]. Kang et al. [21] further proposed a deep sequence-to sequence model based on LSTM and an attention mechanism to improve the landing speed prediction accuracy. These deep learning-based methods not only take advantage of the information at the feature level but also capture the temporal information from these time series flight parameters. Hence, the LSTM-based methods have achieved a good prediction performance. Similarly, for the long landing incident, Wang et al. [22] investigated the correlation between different QAR parameters and a long landing through the analysis of variance method and utilized the logical regression and linear regression models for the long landing risk prediction. Recently, Kang et al. [23] utilized a deep sequence-to-sequence model for long landing prediction, which further improved the prediction accuracy by incorporating an attention mechanism. Predicting aviation safety incidents can enable proactive warnings before safety incidents occur, but these methods cannot help uncover the reasons for safety incidents.

III. PROPOSED SYSTEM

There are three key phases during landing of a flight, i.e., final approach phase, flare phase, and landing phase. In detail, when the aircraft descends to an altitude of about 50 feet above the ground, the pilot will apply back stick inputs to increase the aircraft pitch angle and reduce the vertical speed, to ensure a steady touchdown. After this back stick operation is completed, the aircraft enters the flare phase. Usually, at the beginning of the flare, the aircraft speed is still very high, and it does not touch ground immediately. Therefore, the pilot has to maintain the pitch attitude to make the speed continue to decrease in this phase, so that the aircraft will touch the ground at a relatively small vertical speed. The phase when the aircraft touches the ground and the subsequent movement on the runway until the aircraft ground speed reduces to specific level is called the landing phase.

In this paper, the adverse event is specifically referred to as the events in which the pilot applies forward stick inputs during the flare phase. In this phase, both airspeed and vertical speed of the aircraft gradually decrease, and the lift continues to decrease. In order to make the lift of the aircraft approximately equal to gravity and allow the aircraft to slowly descend close to the ground, the pilot should maintain the pitch attitude of aircraft, help increase the lift to reduce the aircraft's vertical speed, and finally touch the ground smoothly. It is generally required by airlines that pilots should not apply any forward stick inputs during the flare. However, our statistical results from a large number of flights show that this unsafe pilot stick operation occasionally happens. Specifically, from the QAR data of 86,504 flights covering A320 and A321 models at domestic airports in China from May 2017 to December 2018, we observe a total number of 11,385 flight samples with the adverse event. The above unsafe pilot operation may eventually result in an excessive vertical overload at touchdown and cause serious damage to the aircraft's landing gears.

In order to uncover the typical reasons for the adverse event, an innovative approach based on unsupervised K-means clustering algorithm is established in this paper. Our approach is divided into three parts. Specifically, we first preprocess the flight data and select key features based on expert experience. Then, the processed data are input into K-means algorithm to automatically classify them into different clusters. Finally, we investigate the classification results to reveal different reasons for the adverse events. We also analyze the performance of different types of adverse events from different airlines, airports, and pilots.

IV. CONCLUSION

Flight safety plays a vital role in the aviation industry. In this paper, we addressed this issue by investigating pilots' inappropriate stick operation during the flare phase. Specifically, we extracted key features from flight parameters with expert knowledge and took advantage of the K-means clustering algorithm to uncover the reasons for this adverse event. Based on the clustering results, we summarized the reasons into four types, including the headwind influence, high pitch influence, height influence, and pilot personal influence. In addition, we further analyzed the characteristics of the four types of reasons from different airlines, airports, and pilots. The results in this paper can provide researchers with new insights into this problem.

This study is not immune from its limitations. Firstly, our datasets were only for two different airlines. In the future, we will try to incorporate more airlines in our research. Secondly, the methodology in this paper is based on K-means clustering, which has its own limitations. In the future, we will investigate new clustering algorithms to improve the method performance. Lastly, in this paper, we only conducted a data-level analysis with limited domain knowledge. In the future, we will conduct more in-depth research and incorporate more expert knowledge to increase the generality of our results.

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