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## Hybrid safety analysis method based on SVM and RST: An application to carrier landing of aircraft

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#### **ABSTRACT**

To reduce landing mishap risk, one of the greatest challenges is how to accurately determine whether a landing process is safe or not. This paper presents a landing safety analysis method based on a combination of support vector machine (SVM) and rough set theory (RST). In this hybrid approach, the carrier landing data are first analyzed with RST to identify parameters that are sensitive to changes in the state of landing safety. With a landing data set composed of the identified sensitive parameters, the SVM model is trained and the optimal separating hyperplane is obtained to distinguish between the two classes of landing samples (i.e., safe and hazardous), so as to establish the relationship between landing parameters and safety. 635 real landing samples of the aircraft carrier USS Enterprise (CVN 65) are used in the case study, and it is shown that the proposed method is able to identify those parameters contributing more significantly to landing safety and thus deserving more attention paid to. Furthermore, the hyperplane is used as a basis for formulating landing parameter design and control requirements, so that the landing parameters match well and safe landing is guaranteed.

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#### 1. Introduction

Since the advent of the carrier aircraft, people have been making efforts towards improving landing safety, such as the development of equal glide path angle landing technology, the optical landing system, and the Sea-Based Joint Precision Approach and Landing System (JPALS) ([Rife et al., 2008](#page--1-0)). Despite the efforts in making the landing safer, there is still plenty of room for improvement. In the U.S. Navy alone, there were 11 Class A mishaps (mishaps in which the total cost of property damage is \$1,000,000 or greater, or in which an aircraft is destroyed or missing [\(Charlene](#page--1-0) [et al., 2008](#page--1-0))) in the landing process in 2011 and 2012, which caused six casualties ([Naval Safety Center, 2012a, 2012b\)](#page--1-0). According to the statistical data, 80% of mishaps associated with carrier aircraft occurred during landing process [\(Li and Yu, 2006\)](#page--1-0). In the last 20 s especially, there are so ''tightly-coupled'' operations and complex external disturbances that the landing process is vulnerable to failure. Failure during the landing process can even endanger the safety of the aircraft-carrier system in some conditions ([Xu et al., 2012](#page--1-0)). However, improving the performance and reliability of aviation systems is not adequate to solve the problem [\(Leveson, 2011; Morris and Massie, 2010](#page--1-0)); to reduce the mishap risk due to system coupling it is necessary to take timely and effective precautions and corrective measures. Hence, first it needs to accurately analyze the landing process and state within.

Landing process is essentially a motion of an aircraft relative to its carrier, the sea and air. The impacts of personnel, equipment, environment, and some other aspects on landing will eventually be reflected in the changes of landing parameters. These parameters contain dynamic characteristics of the system composed of aircraft, carrier and surrounding environment, so they can be used to analyze landing safety; also these parameters provide significant evidence for prediction and control of landing. Many requirements are described in the landing parameters [\(Navy and Department of](#page--1-0) [Defense, 1993\)](#page--1-0), for example, it is required during landing that ship stern must sink less than 1.5 m, flight deck roll must not be more than  $7^\circ$ , and pitch must not be more than  $2^\circ$  [\(Jiang, 2008](#page--1-0)).

Therefore, the understanding of the relationship between landing parameters and safety is helpful in analyzing landing safety. It would be an ideal situation if their connections are observed through a mechanism, but there are so many influencing factors during landing that strong coupling exists between the parameters and safety. Limited to the current development of technology, it is difficult to build a landing mechanism model with full degree of freedoms (DOFs) which contains all the influencing factors. To discover the connections in mechanism, most models in the previous studies are built with individual influencing factors or limited







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degrees of freedom. For example, in references [Cao et al. \(1995\), Xu](#page--1-0) [et al. \(2010\) and Yu \(2012\)](#page--1-0), the impacts of variable wind field or some other influencing factors on landing safety are presented. The values or safety boundaries of some landing parameters are suggested under simplified conditions by [Chen and Ang \(2011\),](#page--1-0) [Chen et al. \(2011b\), Wang \(2007\) and Xu et al. \(2011\)](#page--1-0). Moreover, studies by [Jiao et al. \(2011\), Shi \(2009\), York and Alaverdit](#page--1-0) [\(1996\)](#page--1-0) and [Zhang et al. \(2009a\)](#page--1-0) have developed simplified local models to simulate landing process and study landing safety.

However, these simplified models tend to have limitations to address the interactions among influencing factors. For example, the risk of landing with both adverse sea conditions and dramatic changes in wind field is not the linear sum of the risks calculated by only considering either, whereas the two conditions often occur simultaneously in reality. On the other hand, it is also important that landing parameters match each other, since only by a reasonable matching among them can a smooth and safe aircraft landing on a carrier be ensured ([Xu et al., 2012\)](#page--1-0).

For the above reasons, many researchers tactfully chose another way to study landing safety, namely, the system identification approach. Based on statistical analysis, the equations describing the relationship between landing parameters and landing safety can be established. These equations can help to analyze and predict landing safety, and they may even assist the landing signal officer (LSO) in making wave-off decision (i.e., landing abortion or not) and thus to minimize crash risks. Moreover, it does not necessarily need to have the intrinsic or fundamental physical mechanism of crash accidents, despite a large number of parameters to be handled as well as their mathematical relationship with landing safety to be explored when using this approach, which means that the landing can be treated as a ''black box'' for which the approach based on data analysis is considerably suitable.

Common mathematical methods include multi-variable statistical analysis ([Tian and Dai, 2014; Tian and Zhao, 2011](#page--1-0)), fuzzy control theory [\(Steinberg, 1993](#page--1-0)), time series analysis ([Blondel et al.,](#page--1-0) [2010; Ma, 1999; Peng, 2006; Yumori, 1981](#page--1-0)), Kalman's optimal filtering theory [\(Sidar and Doolin, 1983\)](#page--1-0) and neural network ([Shi](#page--1-0) [et al., 2006\)](#page--1-0). The landing data are analyzed with one or more of these methods ([Richards, 2002; Tseng and Almogahed, 2009](#page--1-0)) to facilitate safety monitoring and decision-making in the landing process.

However, some difficulties may arise in the application of these methods. Neural network models sometimes fall into a local optimal solution [\(Kim, 2003; Min and Lee, 2005; Olson and Delen,](#page--1-0) [2008; Yang and Liu, 2012](#page--1-0)). In other cases, some assumptions or prior information such as normal distribution assumption [\(Tian](#page--1-0) [and Zhao, 2011](#page--1-0)), stationary random process assumption ([Ma,](#page--1-0) [1999\)](#page--1-0) and LSO's experiences ([Richards, 2002; Shi et al., 2006;](#page--1-0) [Steinberg, 1993](#page--1-0)) are needed before using the related analysis method. Furthermore, those assumptions or prior information may not be precise sufficiently for many landing parameters, or may be difficult to verify. However, the gaps are considered to be filled effectively by rough set theory (RST), as RST can be applied without any problematic necessity of assumptions or information (i.e., not precise enough or difficult to verify) [\(Maaten et al.,](#page--1-0) [2009](#page--1-0)), and can remove redundant information efficiently ([Pawlak, 1984](#page--1-0)). RST, which is not an alternative to the classical set theory but embedded in it, can be viewed as a specific implementation of Frege's idea of vagueness [\(Frege, 1960\)](#page--1-0), i.e., imprecision in RST is expressed by a boundary region of a set, rather than by a partial membership ([Pawlak, 2004](#page--1-0)). The application of RST assists in reaching more objective conclusions ([Dai and Tian,](#page--1-0) [2012\)](#page--1-0), yet definitely RST as such has its deficiencies: weakness of fault tolerance and generalization ([Chen et al., 2011a; Shi et al.,](#page--1-0) [2011; Yang and Liu, 2012; Zhang, 2010; Zhang et al., 2005,](#page--1-0) [2009b](#page--1-0)). By contrast, generalization is exactly a strong point of support vector machine (SVM) [\(Vapnik, 2000; Zhang, 2000\)](#page--1-0). When used for classification, SVM separates a given set of binary labeled training data with a hyperplane that is maximally distant from them (known as the maximal margin hyperplane), so as to implement the structural risk minimization principle for searching to minimize the upper bound of generalization errors rather than minimizing training errors [\(Yang and Liu, 2012](#page--1-0)). On the other hand, the weakness of SVM in removing redundant information from the data set, which may lead to a decrease in the classification performance and an increase in training time [\(Bishop, 1995;](#page--1-0) [Maaten et al., 2009; Song et al., 2005\)](#page--1-0), can be made up by RST ([Maaten et al., 2009; Pawlak, 2004](#page--1-0)). By taking complementary advantages the combination of RST and SVM is capable of yielding more objective and generalized results than either used individually.

Considering the ways that the methods RST and SVM complement each other, this paper presents a landing safety analysis approach integrating both them. Through this approach, the carrier aircraft landing data are used as input, and first analyzed with RST to identify the parameters that are sensitive to changes in the state of landing safety. Next, with a landing data set composed of the identified sensitive parameters, the SVM model is trained and the optimal separating hyperplane is determined to distinguish between the two classes of landing samples ("safe" or "hazardous''), by establishing the relationship between the parameters and landing safety. This hybrid method has the following significance:

- (1) Parameters sensitive to changes in the state of landing safety are identified by the analysis. From the view of safety, the control to the identified parameters should be focused more on during landing than to other ones.
- (2) A safety constraint on ranges of landing parameters changing simultaneously is given and can be referred when designers determine landing parameter and develop control requirements, to ensure that landing parameters well match each other.

#### 2. Analysis method

#### 2.1. Framework

The proposed method combining the advantages of RST and SVM is suitable for analyzing landing data from samples with a large size and multiple features, aiming to establish the relationship between landing parameters and safety based on data mining and statistical learning. The analysis framework is shown in [Fig. 1.](#page--1-0)

First, the landing data are modeled and analyzed by RST. As a starting point, the data are utilized to build a knowledge representation system [\(Pawlak, 1984, 2004\)](#page--1-0), which is also known as a knowledge base or information system similar to an entity-attribute data base. The knowledge representation system is built to facilitate attributes reduction, and to help train SVM model with the aim of obtaining the optimal separating hyperplane. The attributes are classified into two types: landing parameters and the state of landing safety. As entities of the knowledge representation system, the landing samples are described with the values of attributes respectively. This knowledge representation system avoids introducing any problematic information or assumptions; also, the landing parameters are analyzed simultaneously by considering the interactions of influencing factors and the matching among parameters.

Based on the knowledge representation system, the landing-safety-sensitive parameters are determined in the context of remaining landing attributes after reduction, without any significant decrease in its classification performance. The selected Download English Version:

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