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Empirical analysis of air traffic controller dynamics

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ABSTRACT

This paper addresses an empirical analysis of air traffic controller's activities using a human dynamics and complex systems approach. Recent studies on human dynamics show several empirical evidences that, different from common belief respecting random-based Poisson distributions, patterns of human activities fit into power law distribution with heavy tail patterns. Our hypothesis lies upon the question whether or not controller's dynamics obeys the same power law pattern. The analysis based on a 2-weeks simulation dataset is first performed to examine the interaction between traffic activities and controller's communication activities. Two widely studied complexity metrics, the Dynamic Density (DD) and the complexity based on dynamical system modeling (C-DSM) approach, have been constructed from the aircraft trajectory data. It is, however, found that neither the DD nor the C-DSM has significant influence on the controller's communication temporal behavior, except that few approach sectors show close relationships between the DD and communication. Beside this simulation dataset, three other datasets which include another simulation dataset and two operational datasets are also investigated to study the temporal characteristics of controller activities. The use of detrended fluctuation analysis (DFA) found that the inter-communication times of controller are long-rang correlated, showing a heavy tailed pattern. We show that the Inverse Gaussian distribution is better than the Power-law distribution to describe the temporal data. This indicates that the mechanism underlying controller's activities is different from the general one proposed by Barabasi (2005). The Lévy process with positive drift may be capable of explaining the adaptive behavior of the controller.

1. Introduction

Despite the wider and wider range of automation that has been introduced into air traffic management (ATM) systems, scenarios in both SESAR and NextGen concepts still reckon that air traffic controllers continue to constitute the core function of the future system. As the decision-maker and executor of the system, the performance of the controller is closely interconnected with the system safety and efficiency. The prediction of controller's performance with respect to traffic activities is therefore of quantifiable importance.

It has been well known that workload is one of the main factors affecting controller's performance, and some research efforts have been focusing on measuring and predicting controller's workload. Earliest work was based on queuing theory and examination of controller's routine work. A queuing model was proposed by Schmidt et al. based on the hypothesis

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of the single-channel of man's information-processing activity, trying to quantify and predict the workload factors affecting controller's performance (Schmidt, 1978). The prevalent approach to measure workload is based on the controller's subjective rating (Manning et al., 2002). Controllers are asked to report the workload rate that they were experiencing either when they are controlling traffic or just afterwards. On-line ratings could distract the controller from perceiving and controlling traffic and could influence the workload results. Whereas for the workload obtained after work, it may fail to capture the essential property of workload as it emerges from the complex interaction of current traffic situation and controller. In the workload modeling and predicting front, useful information can be found in Loft et al. (2007), in which the authors pointed out the difficulties and shortcomings of existing studies and concluded with several suggestions, leading us to the study of the dynamic properties of workload incorporated with controller strategies management.

There used to be consensus among research and operational communities that the understanding of the factors that drive workload is essential to measure and to predict workload (Averty et al., 2004; Yousefi and Donohue, 2004). Examinations on the relationships between workload and task demands were extensively conducted. Many researchers have tried to demonstrate the complexity factors can reduce sector capacity by increasing controller's workload. These factors can be categorized into three groups, namely traffic factors, airspace configuration factors and operational constraints (Loft et al., 2007). Metrics derived from traffic data, such as Dynamic Density (DD) to indicate traffic complexity, were proposed as an important input for measuring and predicting workload (Laudeman et al., 1998; Sridhar et al., 1998; Masalonis et al., 2003). However, it is found that the performance of DD's predictability greatly depends on time window (Baart, 2001). Chatterji and Sridhar (2001) discussed the shortcoming of complexity equation. One reason is that the non-linear relationship existing between different complexity factors. Another aspect is that the cognitive factor should be considered when analyzing the impact of traffic geometry on air traffic control progress. A brief summary of some relevant work on cognitive complexity is presented by Hilburn (2004). Delahaye et al. (2004) developed a non-linear dynamical systems model to calculate air traffic complexity metric (Delahaye and Puechmorel, 2010). The complexity map can be drawn from the computation of vector field which is obtained from the dynamical system model. Lee et al. (2007) also introduced a "complexity map" that provides complexity for a given traffic situation. Control activity was illustrated in detail in respond to operation environment change. Then a scalar measure of air traffic complexity can be extracted from the complexity map (Lee et al., 2007).

Research on controller's workload, cognitive activities, and air traffic complexity, etc., have been advancing our knowledge of human factors in the ATM system, with the aim of safely enhancing the system efficiency. We should note that both the workload studies and air traffic complexity studies are focusing on the microscopic level of the system, which makes it's difficult to develop a general model being adapting to the whole system. Meanwhile, due to the complicated interaction between air traffic, airspace, and controller's activities, one cannot separate controller from the continuous environment. In the dynamically changed ATM system, there is a lack of understanding of the adaptive behavior of air traffic controller, who acts as a key part of the system. Voice communication, or verbal communication, is the primary means used by controller to control air traffic before the emerging of digital data communication between controller and aircraft, such as Controller Pilot Data Link Communication. However, it is still the only channel for information flow between pilots and controllers in most control centers. Under such circumstance, controller's voice communications activities have direct impact on the system evolution. Therefore, instead of taking their verbal activities as the source of workload, we assume that controller's voice communication are the result of controller's mental and physical efforts after the assessment of current situation according to their experiences.

Analysis of communication data has a long history. In the past, controller's communication events were extensively used to measure workload (Cardosi, 1993; Corker et al., 2000; Manning et al., 2002, 2003; Manning and Pfleiderer, 2006).It should be noticed that the focus these work is the relationship between communication events and workload, rather than the dynamics of the communication activities.

In this article, air traffic controller' communication activities were analyzed from a complex system perspective, to provide an initial demonstration of the physical understanding of the rules by which controller control the traffic. We are interested in the patterns of communications of controllers; in particular the temporal behaviors of the depicted activities under the assumption that voice communications do reflect the activity level of controllers. We are also interested in finding a relationship between controllers' communication activities and traffic activities, knowing that traffic complexity is not necessarily the sole factor that drives controller's communication events but emergencies and non-nominal events, which are randomly distributed. The rest of the paper is organized as following. First, a brief literature review on human dynamics and how it relates to air traffic control are given in Section 2. Section 3 gives general information of the four empirical datasets used in this study. In Section 4 we present the empirical results and discuss the implications of this work. Finally, the conclusion remarks are presented in Section 5.

2. Human dynamics and air traffic controller's voice communication activities

2.1. Heavy-tailed feature of human activities

Until recently, the temporal characteristic of human actions had been thought to be randomly distributed. However, there is increasing evidences showing that the inter-event times, defined by the time difference between two consecutive activities, indeed follow non-Poisson statistical distribution. Heavy-tailed distributions of inter-event times have been widely