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2021

Wee, H. J., Lye, S. W., Pinheiro, J. & Pesquet Popescu, B. (2021). Radar command group time entropy signature as a visual monitoring enhancement for air traffic controllers. IEEE Transactions On Human-Machine Systems, 51(4), 384-393.
<https://dx.doi.org/10.1109/THMS.2021.3076044>

<https://hdl.handle.net/10356/152151>

<https://doi.org/10.1109/THMS.2021.3076044>

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<https://doi.org/10.1109/THMS.2021.3076044>.

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Radar Command Group Time Entropy Signature as a Visual Monitoring Enhancement for Air Traffic Controllers

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Abstract—The activity of generic flight path monitoring of an aircraft on the radar screen is one the major problem which results in air traffic controllers (ATCOs) losing awareness of it. A novel eye signature, known as the radar command group (RCG) time entropy signature, is thus presented in this paper. This signature seeks to model the monitoring behavior of ATCOs using eye-tracking technique during this activity. Acquisition and representation of this monitoring behavior is achieved by first identifying the respective fixation count and mouseover label movement on the aircraft to establish a RCG. The regularity of a RCG exhibited on an aircraft is then calculated using the information entropy formula. Real time simulations are conducted for 88 one-hour experimental sessions with licensed and non-licensed participants comprising of three expertise levels, using scenarios that mimic actual air traffic, consisting of various flight path configuration. Test results of the RCG time entropy signature showed that, an aircraft flying on a flight path with longer distance and no change in altitude likely results in a more regular generic flight path monitoring. Furthermore, it can also be used to differentiate the novice participants from intermediates and experts, as novices lack the training. An ATCO's expertise level can thus be determined and benchmarked accordingly, allowing this signature to be applied on future ATCO training.

Index Terms—Air traffic control, eye tracking, generic flight path monitoring, human-machine interaction, visual monitoring behavior.

I. INTRODUCTION

EYE-TRACKING technique has emerged as the most direct and objective form of measurement of an operator's visual monitoring behavior [1]. It is used as a method for monitoring and analyzing the viewing behavior of an operator in various surveillance fields like air traffic control (ATC) [2], [3], driving [4], pilot assessment [5], and healthcare [6]. It is also found to

be able to identify and model the cognitive activities of these operators [7], [8], as it contains rich and complex information regarding a person's interest and implicit intentions when viewing or searching the same visual scene [9], [10]. Therefore, researchers in ATC are also using eye-tracking techniques to model and understand the monitoring behavior of air traffic controllers (ATCOs) [2], [3].

In recent years, 4-dimensional trajectory-based operations (4D-TBO), where the flight trajectory of an aircraft can be predicted in a timely, accurate, and consistent manner, has been adopted in ATC. Aircrafts are thus, freer to fly on their own desired trajectories, creating a more complex air route structure with tighter separation standards [11], [12]. Radar ATCOs are required to monitor the aircraft, create and maintain a mental picture of where the aircraft were on the radar screen, in their tactical monitoring activities [13].

Research reports listed six main causal factors influencing operational errors (OE) of ATCOs [14], where a distribution of these causal factors found radar display error to be the most, at 58.7% [15]. Misidentification and inappropriate use of displayed data were found to be the key contributing factors of radar display error, while 95% of them are related to an individual's attention and memory [16]–[18]. The most significant cognitive error involves perception and vigilance errors like no and late visual detection, forgetting previous actions, in an ATCO's radar monitoring tasks [15], [19], [20]. Similarly, using Endsley's situation awareness (SA) model [21], perception (Level 1 SA) and comprehension (Level 2 SA) when combined constitute 88% of SA errors, which consists of errors like failure to monitor or observe data and difficulty to detect and perceive data [22]. Such findings remain relevant till today [23]. Additionally, incident reviews have highlighted lack of aircraft awareness and experience of ATCOs in the generic flight path, tactical radar monitoring tasks as reasons for loss of separation and ineffective monitoring.

As a result, problems like failing to observe the appropriate flight parameters or data on the radar display in a regular and consistent fashion, due to the unawareness on the generic flight path of an aircraft on the radar by ATCOs, persists. This challenge is further compounded owing to performance degradation, fatigue, and variation amongst ATCOs in an increasingly foreseeable congested airspace. Therefore, it is crucial to capture and model how an ATCO perceives and comprehends the different radar elements on the radar screen, to maintain their awareness of the generic flight path monitoring of aircraft flying in the airspace

Manuscript received April 6, 2020; revised November 20, 2020 and February 7, 2021; accepted March 28, 2021. Date of publication May 24, 2021; date of current version July 19, 2021. This work was supported in part by Thales Solutions Asia Pte Ltd, under the Economic Development Board, Industrial Postgraduate Programme, with Nanyang Technological University, Singapore. This article was recommended by Associate Editor M. L. Bolton. (*Corresponding author: Hong Jie Wee.*)

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Color versions of one or more figures in this article are available at <https://doi.org/10.1109/THMS.2021.3076044>.

regularly [24]. This is even more critical in future, as tactical complexity is increasing and ATCOs shift toward a more active monitoring role.

II. LITERATURE REVIEW

Techniques developed and used by researchers to capture and model an ATCO's perception and comprehension of the different radar elements on the radar screen are reviewed.

Several of these techniques come in the form of self-rating by the ATCO, or assessor rating scored by subject matter experts (SMEs). Situational awareness rating technique (SART), is a multidimensional, self-rating technique aimed at measuring the perception and comprehension level of ATCOs [25]. ATCOs are to rate their understanding of the situation based on the tasks performed, at the end of every exercise, before an overall score is being calculated.

As SART is conducted at the end of exercise, it will not disrupt an ATCO's natural flow of task. Being a self-rated assessment, changes in an ATCO's perception and comprehension would not be detected as it is not directly detecting where and what the ATCO is looking at, making an in-depth study to characterize the visual monitoring of this activity not possible. Furthermore, SART is also subjected to various forms of biasness as it is dependent on an ATCO's interpretation. This further supported by the fact that participants are poor at reporting detailed information about past events and they tend to not recall periods of tasks when they possess low SA [26].

Situational awareness global assessment technique (SAGAT) is another well-established technique to determine an ATCO's perception and comprehension level. This is achieved by raising queries of the ATCOs' perception of the simulation through pauses at random timings, reflecting their perception and comprehension level [27], [28]. Responses were then marked as correct or incorrect accordingly. Many research studies performed using SAGAT reported high validity and reliability [21], [29].

SA for SHAPE (SASHA) is another popular technique which comes in the form of online queries and postexercise questionnaire [30]. SASHA on-Line (SASHA_L) requires an SME to pose queries in real time based on how the scenario unfolds on the ATCO's screen. ATCOs are rated based on their answer's accuracy and response time. For SASHA questionnaire (SASHA_Q), it is designed based on well-recognized human factors principles and ATCOs are required to complete the questionnaire at the end of the simulation. Hence, SASHA can provide a detailed assessment of an ATCO in real time, while having the advantage of both online assessment and post questionnaire.

Measures like SAGAT and SASHA are more reliable, as they are not subjected to the interpretation of SMEs or ATCOs [31]. They are also sensitive to changes in an ATCO's perception and comprehension throughout the duration as the queries can be made more frequently [26]. However, these are not direct measurements of how an ATCO perceives the radar elements and comprehend them, as these are evaluated through the response of the real-time probing and querying of ATCOs. In doing so, changes in the ATCO's perception and comprehension level are

unexplainable. Furthermore, both SAGAT and SASHA could disrupt an ATCO's natural flow of tasks and possibly direct their attention to the required elements, causing biasness in return.

Eye-tracking techniques are also used to capture and evaluate the perception and comprehension level of ATCOs. In ATC research, wearable eye-tracking techniques are normally used for understanding an ATCO's attention allocation on the new tool introduced in their working environment. Rovira *et al.* used it to determine an ATCO's attention allocation of a new tool in the ATC area control environment [32]. ATCOs are found to look at the radar display more often whenever there is imperfect automation, indicating that they were not aware of the new tool. Moehlenbrink used a head-mounted eye-tracking system to determine the best multiple remote tower setting by understanding where ATCOs tend to look to best arrange their working position [33]. A study to compare the cognitive strategies of novice ATCOs to resolve conflict was conducted using an eye tracker with a chin rest, and several eye metrics were used [2]. Results of this study indicate a better attention control, attention resource allocation, and efficient information processing by expert ATCOs, as compared to novices. Such is attributed to the expert ATCOs showing better cognitive strategies in the resolving of conflicts.

In these studies, wearable eye-tracking techniques are mainly used to determine an ATCO's visual attention and usage of a new tool or their perception in conflict situation. Consistent eye-tracking results being generated show that it is reliable and not subjected to biasness. A continuous measurement of these eye-tracking signals throughout the entire experimental duration enables sensitivity in detecting changes of how an ATCO looked. This illustrates that eye-tracking technique can capture an ATCO's perception level. Although pose estimation methods can be used to map static objects to eye movement [34], these eye-tracking techniques are unable to do so for a dynamic radar display. Hence, they are lacking in the acquisition and representation of an ATCO's comprehension level, before explaining it. Furthermore, these techniques are obtrusive and cause discomfort, which could possibly affect the way ATCOs work, interfering with the primary tasks.

Remote eye-tracking techniques are also used to assess the visual monitoring behavior of ATCOs. Imants *et al.* used various fixation derived eye metrics to determine the tasks performed by the ATCO, their workload and efficiency of visual search, to support the use of automation in future [35]. Using a remote eye tracker, Kang *et al.* used scanpaths to determine the visual scanning of an ATCO on a radar screen. A maximum transition-based agglomerative hierarchical clustering (MTAHC) algorithm is derived to capture and evaluate the visual monitoring behavior of ATCOs in conflict detection tasks, by understanding if the participants managed to detect and correctly identify a conflicting aircraft pair. Through this visual monitoring behavior, ATCOs were classified according to their expertise level [36]–[39]. Wang *et al.* used a remote eye tracker and applied the multifractal detrended fluctuation analysis (MDFFA) method on the time series data of fixation and saccades to show that working experience has effects and a correlation on eyeball movement of ATCOs [40]. It is also found that an experienced ATCO tends to

TABLE I
EVALUATION OF REVIEWED TECHNIQUES TO CAPTURE AND MODEL AN ATCO'S PERCEPTION AND COMPREHENSION

Measurement Techniques	Consistent, not subjects to biasness	Accurately detect and identify changes for specific intent	Non-disruptive	Non-intrusive	Continuous across time
SART	✗	✗	✓	✓	✗
SAGAT	✓	✗	✗	✓	✓
SASHA	✓	✗	✗	✓	✓
Rovira et. al	✓	✗	✓	✗	✓
Moehlenbrink et. Al	✓	✗	✓	✗	✓
Taukuri et. al	✓	✗	✓	✗	✓
Imants et. al	✓	✗	✓	✓	✓
MTAHC by Kang et. Al	✓	✗	✓	✓	✓
MDFA by Wang et. Al	✓	✗	✓	✓	✓

fixate more on important regions of the radar screen and fixation duration and saccadic velocity are crucial indicators to examine the expertise level of an ATCO [41].

Such remote eye-tracking techniques are found to be suitable in determining the perception level of ATCO. They can pinpoint where the ATCO is looking at on the radar screen in a non-intrusive manner, not disrupt their primary task, while tracking their changes in perception continuously across time. Consistent results with similar trends and findings were observed. However, these measurements usually depict if ATCOs are looking at certain elements and regions of the radar screen, with narrow understanding in the changes of their monitoring behavior. Furthermore, they are also limited to explaining the changes in the perception and comprehension of ATCOs, as they are unable to correlate to the different elements of the radar screen for a finer representation of an ATCO's monitoring behavior on various air traffic situation.

A. Evaluation of Eye-Tracking Techniques in ATC

In the generic flight path of aircraft via radar surveillance, an ATCO is required to have a good perception and comprehension of the different radar elements and traffic picture before executing the necessary actions timely. Therefore, this measurement should be consistent and not subjected to any form of biasness, accurately detect and identify changes in how an ATCO perceives and comprehends radar elements for specific intent, while not disrupting them in order to capture effectively. In addition, this measurement should also be nonintrusive while measuring eye movement continuously across time. These measurements are also similar to that of a good SA measure. Using these five desired criteria, the reviewed eye-tracking techniques are being evaluated and shown in Table I.

From Table I, all reviewed measurement techniques lacked the ability to accurately detect and identify changes for specific intent, to determine how an ATCO is looking and behaving throughout their tactical monitoring activity. This is important as changes in an ATCO's monitoring behavior needs to be detected accurately, to understand and characterize how an ATCO maintains their awareness of the generic flight path monitoring of an aircraft. As a result, this evaluation showed that there is a need to develop a new, real time measurement to capture an ATCO's perception and comprehension level in the generic flight path monitoring of an aircraft that can detect and identify how an ATCO maintains their awareness by looking at an aircraft continuously, while fulfilling all other remaining criteria.

Fig. 1. Overview for the formulation of RCG time entropy signature for generic flight path monitoring.

III. VISUAL SIGNATURE CAPTURE FOR THE GENERIC FLIGHT PATH MONITORING BEHAVIOR

The generic flight path monitoring of an aircraft in the airspace is being listed as one of the relevant tactical monitoring activities in future ATCO operations [13]. For this tactical monitoring activity, an aircraft is flying along the designated airway in the ATCO's sector of control. This aircraft will fly along this airway from acceptance to handing over, which also involves either a changing flight level (FL) flight or cruising flight. To manage the generic flight path monitoring of an aircraft, an ATCO would likely have fixated on the aircraft's label deliberately while performing a mouseover, on several occasions throughout the course of its flight, to be aware of the aircraft's flight state. This mouseover action is essential, as it represents that the ATCO hovering across the aircraft's label look at the information on it intentionally, as well as executing radar commands (clearances) to the aircraft based on the situation. As a result, the proposed visual signature to capture the generic flight path monitoring behavior of ATCOs should involve the combination of both eye and hand movement data of the ATCO, together with the time (instance) when such an action is executed.

As generic flight path monitoring is a multitasking activity, ATCOs would need to distribute this activity evenly among the different aircrafts, to maintain their overall awareness of all aircraft on the radar display [38]. For an ATCO to manage this multitasking activity, they are only required to be monitoring any aircraft intermittently in a regular fashion [13], [42]. Hence, it is essential to track the regularity of this activity.

Therefore, a generic flight path monitoring signature, herein known as radar command group (RCG) time entropy, is proposed to capture the perception and comprehension level of ATCO for the generic flight of an aircraft across the airspace. Using this signature, the regularity of an ATCO monitoring an aircraft on its flight path is also determined. Fig. 1 shows an overview of the formulation of this signature, which consists of three different phases. Phases 1 and 2 seek to identify and construct an RCG, while phase 3 involves the calculation of the RCG time entropy value, which quantifies the regularity of the generic flight path monitoring activity.

Fig. 2. Time series plot of an ATCO's eye and hand movement for Aircraft A.

A. Phase 1: Identification of RCG

In phase 1 of this formulation of RCG time entropy signature, an RCG is first defined. To do so, the activity of an ATCO looking at an aircraft deliberately and performing a mouseover are being captured. For a fixation exhibited by an ATCO, it is first matched to the corresponding flight object of an aircraft on the radar screen. Such is achieved using the “dynamic data alignment and timestamp synchronization” model [43], and the fixation and its corresponding duration exhibited is then matched to the frame number. It is important to note that the frame number represents the number of frames elapsed since the start of the radar simulation with each frame being the duration of each revolution. Similarly, the mouseover action exhibited by a participant for the purpose of looking intentionally or issuing radar commands is also being captured and matched to the respective frame numbers.

An arbitrary aircraft A is used to illustrate the different fixation and mouseover actions exhibited by an ATCO. The different possible radar command actions are mouseover of aircraft label to select it (SAA), issuing clearances like taking jurisdiction of aircraft upon entry to sector (UCO), handing over the jurisdiction of an aircraft upon leaving sector (TOC), clearing an aircraft to climb or descend to a specific FL (EFL), clearing the aircraft to fly on a specified heading (HDG), changing the exit FL (XFL), and also to move the label of the aircraft. Hence, a time series of an ATCO's fixation and mouseover action on Aircraft A's label were superimposed and plotted across time, as seen in Fig. 2.

In Fig. 2, each blue dot represents a fixation, with its value corresponding to the elapsed time in seconds and also its fixation duration in milliseconds (ms). Subsequently, each vertical line represents a radar command, while different colors show its corresponding command issued. From Fig. 2, it is observed that there are several instances where an ATCO exhibits fixation and mouseover of aircraft label closely in time, while there are other instances where fixations occur with no mouseover of label and vice versa. This indicates that whenever fixations and mouseover occur very close in time, the ATCO is active in deliberately fixating on the aircraft, to maintain his awareness of it or to issue appropriate commands, for its generic flight path monitoring. Observations of the different mouseover of label with fixations occurring shows its occurrence intermittently.

Based on these observations, an RCG can thus be identified as a fixed time interval that consists of one or several mouseover

Fig. 3. RCG time profile for Aircraft A of an ATCO.

of an aircraft label, with at least one fixation within it. This time interval is set using the timestamp of the first and last of such mouseover labels, before adding a half frame tolerance, as fixations on the aircraft could happen slightly before and after a mouseover label event. It is important to note that other radar commands occurring in the same frame are grouped together in the same RCG.

B. Phase 2: Construction of RCG Time Profile

In phase 2, the different RCGs present in the generic flight path of an aircraft can be plotted across time, together with its corresponding sum of fixation count and fixation duration, as the aircraft flies across its flight path in the sector. Fig. 3 shows an example of an RCG time profile of an ATCO for aircraft A. Different RCG types are labeled with a different color, with each color signifying key tasks that the ATCO is executing. The three key tasks relevant in future are, namely, “crossing monitoring,” “UCO,” and “TOC.” The other RCG not belonging to these three key tasks are labeled as “Generic.” If there are two out of the three key tasks occurring at the same RCG, a separate color is assigned to it. Hence, a total of six different RCG types were derived accordingly.

From Fig. 3, it is observed that the ATCO has exhibited all three key tasks in their RCG time profile. By comparing the fixation count and fixation duration of each RCG, the RCG at frame 52 (crossing) has more fixation duration than fixation count. Deeper investigation revealed that at this RCG, the participant is issuing a clearance for aircraft A to climb, thereby requiring more information processing. Based on the RCG time profile in Fig. 3, RCGs were exhibited by the ATCO across the entire sector occupancy of an aircraft. As a result, it can be postulated that for an ATCO to be perceiving and comprehending an aircraft regularly for a generic flight path monitoring task, there should be a minimum number of RCGs, which is occurring regularly across the time profile.

C. Phase 3: Calculating RCG Time Entropy

In phase 3, the RCG time profile can be evaluated by assessing the number of RCGs and the consistency (regularity) of the RCG time profile, to determine if an ATCO has fixated on the aircraft's label deliberately throughout the course of its flight across the

airspace sector. To do so, information entropy of the RCG time profile is calculated.

In the last twenty years, the use of entropy methods to define periodicity or regularity in human data is increasingly popular [44]. Entropy has been used to describe changes in human physiological signals like postural control [45] as well as movement tasks [46]. Information entropy by Shannon is a foundational concept of information theory which quantifies the amount of information in a variable [47]. This amount of information is not just a count of the information available it is also proportional to the amount of “surprise” (gain) of the information. Hence, Shannon’s information entropy quantifies the absolute minimum amount of information (knowledge) gain. Information gain is defined as the inverse of probability of an event occurring, where the lower the probability of an event occurring, the larger the information gain, as seen in (1). In (2), Shannon’s information entropy is shown, and it is equal to the sum of probability of information gain from all events. It is also observed from (2) that information entropy considers both the quantity and quality of information gained

$$I_i = \frac{1}{p_i} \quad (1)$$

$$H(p) = \sum_{i=1}^n p_i \log I_i = - \sum_{i=1}^n p_i \log p_i \quad (2)$$

where H , I , p represents information entropy, information gain, and probability, respectively.

Information entropy has been applied on many applications involving discrete signals, like financial data analysis, computing networks, and many more [48], [49]. A discrete signal source is defined as a system producing a sequence of symbols governed by a set of probabilities [50]. Hence, the process of determining if an RCG exists across an aircraft’s flight in a sector at any point of time is a way to discretize the continuous eye and hand movement of a participant. Therefore, information entropy can be applied on the RCG time profile of an ATCO, where higher information entropy meant more information gained by an ATCO on the aircraft during its generic flight monitoring activity.

Using information entropy to compute the regularity of an RCG time profile, the duration of aircraft in the sector is first computed. Subsequently, the time difference between individual RCG across time is calculated by taking the difference in the frame number between the end of current RCG and the start of the next RCG. A reference RCG is positioned intentionally at the start and end of every flight path profile for the information entropy computation, to denote the instant when the aircraft enters and leaves the airspace, respectively. From the list of time differences, the probability of each time difference occurring is calculated using (3), before applying it to (2)

$$\text{Probability} = \frac{\text{Time Difference}}{\text{Flight Duration}}. \quad (3)$$

Using this calculation of information entropy to quantify the regularity of an RCG time profile, a set of information entropy values for different RCG time profiles is calculated, to determine

Fig. 4. Illustration of different RCG time profile cases with their respective information entropy value.

the RCG time entropy value, in order to interpret them meaningfully. Fig. 4 provides a description of these different cases of RCG time profile and its corresponding RCG time entropy value for Aircraft X, with the same start and end reference frame.

By comparing cases 1 and 2, cases 3 and 6, one extra RCG results in a higher information entropy value, given the same time interval between individual RCGs. This is reflective of a regular generic flight path monitoring, as every new RCG results in more information gain by the ATCO. A larger duration between RCGs results in a larger entropy value, as seen in the comparison between case 2 (18 frames) and 3 (4 frames). This is reflective of the need to monitor the aircraft more regularly during its flight, as monitoring it more closely in time without monitoring it again results in less information gained. Furthermore, by comparing cases 3, 4, and 5, where all four RCGs are spaced 4 frames apart individually, a first RCG occurring 39 frames after an aircraft enters the sector results in a higher information entropy value as opposed to the first RCG occurring 1 frame and 77 frames after an aircraft enters the sector. Such observation is also reflective of the regularity in the generic flight path monitoring of ATCOs, as the information gained by an ATCO only when he/she monitors early or late is lesser as compared to one who monitors in the middle. Lastly, case 7 shows an RCG time profile, with 6 RCGs that are randomly spaced. It has the highest information entropy value among all the cases and reflective of a regular generic flight path monitoring of an ATCO, by monitoring throughout the flight path profile regularly, with the intervals spaced randomly.

Therefore, a higher RCG time entropy value signifies that an ATCO has fixated on the aircraft’s track or label deliberately more regularly, by either exhibiting the RCG more often or more consistently throughout the course of its flight. A higher RCG time entropy value would signify a greater intent to maintain a higher level of awareness, exhibiting a more regular generic flight path monitoring behavior from an ATCO. For Aircraft A, the RCG time entropy value is 1.79.

Fig. 5. Standard controller working position (CWP) with remote eye tracker.

IV. EXPERIMENTAL SETUP AND SCENARIO DEFINITION

An experiment was conducted to determine if the RCG time entropy signature can differentiate the generic flight path monitoring behavior of ATCOs due to expertise level and flight path configurations. Such could help in curating the training of prospective ATCOs, and aiding ATCOs operationally.

A. Experimental Setup

To conduct the experiments, a real-time simulator, the NLR ATM Research SIMulator (NARSIM), was used to generate and simulate air traffic scenarios in real time, with every radar update at 9.8 s. Pseudo pilots were used to facilitate the flying of the aircraft, by following the same scenario script, so that events in the same scenario occurred at the same instant. A standard controller working position (CWP), consisting of a 2K radar screen (50 by 50 cm, equivalent to 20 by 20 inches) was used to display air traffic data in a given airspace sector, as seen in Fig. 5.

A remote eye tracker, Tobii X2-30 was used to capture the eye data of the participants in a nonintrusive manner. In this setup, the eye tracker is positioned 18 cm in front of the screen, 55 cm from the participant's eye, to extend the eye tracker's field of view so that gaze data on any regions of the 2K screen can be captured. This meant that the eye tracker is deployed in a nonideal condition that closely mimic the ATCOs' working environment. Hence, the accuracy and precision of this eye tracker is determined prior to this study, at this nonideal condition. For a total of 3128 gaze data samples, the accuracy and precision of the Tobii X2-30 was found to be 3.5° (3 cm) and 1.1° (1 cm), respectively, with good validity of 93.7%. These values of accuracy and precision of the Tobii X2-30 is quite close to that reported by Clemotte *et al.*, which is 2.5° and 2.0° , respectively, performed using for the same eye tracker model under nonideal conditions [51], [52].

Raw eyeball movement and radar data are then extracted from the Tobii X2-30 and NARSIM, respectively, via an intelligent real-time post processing server, using the "dynamic data alignment and timestamp model" [43]. Such ensures that the two data streams are synchronous in time and space. The two sets of extracted data are then computed to determine the various eye-tracking metrics. Using the I-VT algorithm, the velocity

threshold for fixation determination is $105^\circ/\text{s}$ [53], and the new boundaries of an aircraft's track and label for the mapping of a fixation were a 70-pixel diameter and 230-pixel diameter circle, respectively. These eye metrics which were mapped to a flight object on the radar screen were then relayed to the Thales TopSky-HF software to record the data of the different test participants [54], [55].

B. Experimental Sessions

88 one-hour experimental sessions, with one participant per session, were conducted among male participants whose ages varied between 24 and 41 ($M = 29$, $SD = 5.34$). Participants were classified into two license levels (licensed, nonlicensed), which also comprises of three different expertise levels (novice, intermediate, and experts), based on internationally recognized framework (ICAO standards) [56]. Hence, there are 44 licensed and 44 nonlicensed sessions, where the nonlicensed sessions contain 24 novice and 20 intermediate sessions, while all 44 licensed session are expert sessions.

C. Experimental Procedure and Scenario Definition

Prior to the experiment, each participant involved in a session underwent an initial 9-point eye-tracker calibration exercise. Calibration was repeated until a satisfactory calibration was obtained that refers to Tobii Studio's qualitative calibration report.

Real time simulations were conducted for 88 one-hour experimental sessions, with different scenarios consisting of 60 aircrafts that mimics operational air traffic and is approximately to 1.2 times of the regular traffic volume in area control (upper airspace sector). During these sessions, participants are required to guide these aircrafts to fly across the airspace of interest (sector) safely. To do so, they need to monitor the aircraft on the radar display, ensure that these aircrafts conform to their flight requirements, such as entering and exiting the airspace at specified flight level while flying on the designated airway. At the same time, participants also need to manage the potential conflicts arising from guiding these aircrafts, ensuring safety constantly. At any point of time, participants could issue instructions to an aircraft, by talking to pseudo pilots via radiotelephony.

In this sector, there is a mixture of different airway lengths with an aircraft needing to climb or descend. For each scenario, each aircraft would enter and exit the sector at different random timings, while facing a crossing traffic with another aircraft at random instances. There are a total of 10 airways ranging from 11 to 70 NM, 21 crossing points, 11 to 36 aircrafts on the radar display at any point of time, while undergoing FL changes from -90 to 90 . Such specifications meant that the scenario designed is of a very complex sector, as other studies involving ATC real time simulations usually uses airspace sector that comprise of less than 10 crossing points and aircraft at the regular traffic volume [35], [39]. The airspace of interest in this real time study was based on an existing airspace sector, with information referenced from the publicly available SkyVector website [57].

Every participant would have encountered the same number of flight path configuration and crossings, fulfilling a within-subject design. Participants maintained the same operational

TABLE II
DESCRIPTION OF DIFFERENT FLIGHT PATH CONFIGURATION

Flight path configuration	Flight Distance (NM)	Change in FL	Number of Crossing	Flight Segment
1	228	0	1	Entry > Airway > Crossing > Airway > Exit
2	108	-40	1	Entry > Crossing > Exit
3	123	70	1	Entry > Crossing > Airway > Exit
4	110	100	1	Entry > Airway > Crossing > Exit

performance for every scenario, as there is no loss of separation between the aircraft found and all aircraft entered and left the airspace at the designated flight levels. All these happened while participants are not being distracted.

V. RESULTS AND DISCUSSION

The generic flight path monitoring activity is characterized by the length of its flight along the designated airway, changes in flight level, and the different flight segments [13]. Studies have shown that in such a complex sector, an ATCO is expected to monitor more regularly and consistently with a longer flight distance and no change in FL. Furthermore, it is also found that participants of a higher experience level tend to exhibit more regular generic flight path monitoring of an aircraft in a complex sector [13], [38]. Hence, four flight path configurations, each with only one crossing, were chosen within the scenario, as they cover a wide spectrum of the various characteristics of the generic flight path monitoring activity. This is described in Table II.

A. Effect of License Level and Flight Path Configuration

The effect of experience (license level) and flight path configuration on the generic flight path monitoring behavior of participants is analyzed using the proposed RCG time entropy signature. This is applied on 12 selected aircrafts in each session, covering the four flight path configurations described in Table II. To study this effect, 132 nonlicensed and 132 licensed instances were selected, where one instance comprised of one aircraft on one flight path configuration.

To compare these differences, descriptive statistics (sample size = N , mean = M , standard deviation = SD) of the RCG time entropy values were first listed in Table III. As the sample sizes for each flight path configuration and license level is the same, the homogeneity of variance assumption was met. Furthermore, normality is also assumed with more than 30 instances for each level of comparison. A two-way mixed factors ANOVA was then conducted to examine the effect of flight path configuration and license level on RCG time entropy value, where a corresponding p -value < 0.05 , indicates significance at 95% confidence. A Greenhouse–Geisser is used to obtain the p -value if the sphericity assumption was not met. A Tukey's honestly significant difference (HSD) post hoc test was then performed

TABLE III
DESCRIPTIVE STATISTICS OF THE RCG TIME ENTROPY VALUE FOR THE DIFFERENT FLIGHT PATH CONFIGURATION ACROSS LICENSE LEVEL

Flight path configuration	Non-licensed	Licensed
1	$N = 33, M = 2.24, SD = 0.546$	$N = 33, M = 2.12, SD = 0.336$
2	$N = 33, M = 1.68, SD = 0.550$	$N = 33, M = 1.63, SD = 0.467$
3	$N = 33, M = 1.41, SD = 0.842$	$N = 33, M = 1.83, SD = 0.505$
4	$N = 33, M = 1.62, SD = 0.535$	$N = 33, M = 1.83, SD = 0.388$

to determine where the differences occurred between the flight path configurations, as there are more than three groups.

Results from the two-way mixed ANOVA test showed a statistically significant interaction between the effects of flight path configuration and license level on RCG time entropy value, Greenhouse–Geisser $F(2.55, 161) = 24.8, p < 0.001$. Simple effects analysis showed that licensed participants have significantly higher RCG time entropy value as compared to nonlicensed participants for only flight path configuration 3 ($\Delta = 0.423, p = 0.002$). For licensed participants, a significantly higher RCG time entropy value is seen when comparing flight path configurations 1 and 2 ($\Delta = 0.555, p < 0.001$), 1 and 3 ($\Delta = 0.824, p < 0.001$), 1 and 4 ($\Delta = 0.618, p < 0.001$), 2 and 3 ($\Delta = 0.269, p = 0.044$). For nonlicensed participants, a significantly higher RCG time entropy value is seen when comparing flight path configurations, 1 and 2 ($\Delta = 0.484, p < 0.001$), 1 and 3 ($\Delta = 0.282, p = 0.035$), 1 and 4 ($\Delta = 0.291, p = 0.03$).

These results show that there is insufficient evidence to indicate a difference in generic flight path monitoring behavior between the license levels of the participants, as significantly higher RCG time entropy value is only observed for flight path configuration 3. Moreover, there is enough evidence to indicate a difference in generic flight path monitoring behavior between the flight path configurations, where all participants exhibited a higher RCG time entropy value for flight path configuration 1 as compared to 2, 3, and 4.

B. Effect of Expertise Level and Flight Path Configuration

Further analysis was performed using expertise level instead of license level for the participants, to further analyze the effect of experience and flight path configuration on the generic flight path monitoring behavior of participants. Using the same aircraft in Table II and a total of 72 novice, 60 intermediate, and 122 expert instances, descriptive statistics of the RCG time entropy values were listed in Table IV.

With different sample sizes for expertise level, Levene's F test was performed to determine if the homogeneity of variance assumption was met [58]. Similarly, a two-way mixed factors ANOVA was then conducted to examine the effect of flight path configuration and expertise level on RCG time entropy value, while the Tukey's HSD and Games Howell post hoc test was used when homogeneity of variance was met and not

TABLE IV
DESCRIPTIVE STATISTICS OF THE RCG TIME ENTROPY VALUE FOR THE
DIFFERENT FLIGHT PATH CONFIGURATION ACROSS LICENSE LEVEL

Flight path configuration	Novice	Intermediate	Expert
1	N = 18, M = 2.10, SD = 0.629	N = 15, M = 2.40, SD = 0.384	N = 33, M = 2.12, SD = 0.336
2	N = 18, M = 1.56, SD = 0.597	N = 15, M = 1.82, SD = 0.469	N = 33, M = 1.63, SD = 0.467
3	N = 18, M = 1.17, SD = 0.926	N = 15, M = 1.70, SD = 0.647	N = 33, M = 1.83, SD = 0.504
4	N = 18, M = 1.53, SD = 0.568	N = 15, M = 1.71, SD = 0.493	N = 33, M = 1.83, SD = 0.388

met, respectively [59], [60]. A corresponding p -value < 0.05 , indicates significance at 95% confidence.

Unequal variances for expertise level were shown using Levene's test, $F(11, 252) = 3.30$, $p < 0.001$. Results from the two-way mixed factors ANOVA test showed a statistically insignificant interaction between the effects of flight path configuration and license level on RCG time entropy value, Greenhouse–Geisser $F(5.10, 161) = 2.16$, $p = 0.061$. Hence, the main effects of the two factors were studied, where significant differences were observed for the effect of expertise level, $F(2, 119.15) = 4.23$, $p = 0.017$ (Welch) and the effect of flight path configuration, $F(3, 252) = 17.1$, $p < 0.001$. Significantly lower RCG time entropy values were observed between novice and intermediate ($\Delta = -0.315$, $p = 0.020$), novice and experts ($\Delta = -0.260$, $p = 0.025$), while a significantly higher RCG time entropy value is observed for when comparing flight path configurations, 1 and 2 ($\Delta = 0.520$, $p < 0.001$), 1 and 3 ($\Delta = 0.553$, $p < 0.001$), 1 and 4 ($\Delta = 0.454$, $p < 0.001$).

As a result, there is sufficient evidence to indicate a difference in generic flight monitoring behavior between the flight path configurations and expertise levels, where all participants exhibited a higher RCG time entropy value for flight path configuration 1 as compared to 2, 3, and 4, while novices exhibited a lower RCG time entropy value as compared to intermediates and experts.

C. Discussion

Results from both analyses were consistent in indicating that a longer flight distance with no change in FL (flight path configuration 1) likely results in a more regular generic flight path monitoring of an aircraft, whereas a shorter distance and changing FL (flight path configuration 2, 3, and 4) requires lesser regularity in the generic flight path monitoring of an aircraft. This is consistent with other studies, where altitude information is observed prior to any other information for conflict detection [61], [62]. Hence, a need to change FL likely results in conflict detection behavior first (which is a different mode of visual monitoring behavior), as opposed to the generic flight path monitoring, thereby resulting in a lower RCG time entropy value, for flight path configuration 2, 3, and 4.

Comparing the experience level of participants, results obtained using license level did not show a difference in the generic

flight path monitoring, while results using expertise level show that novices are less able to perform a regular generic flight path monitoring of an aircraft, as opposed to intermediate and experts. This difference in results when comparing license and expertise levels suggest that intermediate participants could likely maintain their awareness on the generic flight path monitoring of an aircraft at about the same level as experts, thereby causing this difference when grouped together with novices as the nonlicense group. This is consistent with the results of Wang *et al.*, where experienced ATCOs tend to fixate on more important, task-relevant area of the radar screen [40]. It is also consistent with studies indicating participants of higher experience exhibiting a more regular generic flight path monitoring of an aircraft in complex sector [13], [38]. Hence, this result highlights the ability of the RCG time entropy signature in identifying novices from intermediates and experts.

VI. CONCLUSION

A novel eye signature for ATCOs, known as the RCG time entropy signature, is presented in this article. This signature seeks to model the monitoring behavior of ATCOs for the activity of generic flight path monitoring, by using RCG, which comprises fixations and mouseover label actions occurring in an aircraft closely in time. The regularity of an ATCO's generic flight path monitoring behavior is determined by first constructing an RCG time profile before evaluating it using the information entropy. This signature could indicate how frequent and regular an ATCO had perceived and comprehended the aircraft on its generic flight path, where a larger RCG time entropy value represents a higher level of regularity and consistency of the RCG time profile.

Experiments conducted on 12 selected aircrafts of four different flight path configurations using a real time, high-fidelity simulation showed a difference in the generic flight path monitoring behavior due to expertise and flight path configuration.

Test results showed novice participants lack the training and expertise to perform a regular generic flight monitoring of an aircraft, while intermediate participants are able to maintain their awareness at about the same level of experts. Such is seen in the differences in monitoring behavior when novice participants are not grouped together with intermediates while comparing with experts. Furthermore, it is found that an aircraft flying on a flight path with longer distance and no FL change likely results in a more regular generic flight path monitoring. These results are also consistent with other studies, where ATCOs tend to monitor an aircraft with altitude change needed with conflict detection behavior first, as opposed to generic flight path monitoring, whereas a higher expertise levels results in a more regular generic flight monitoring behavior.

Therefore, these results showed that the RCG time entropy signature is a suitable measure for understanding differences in an ATCO's generic flight path monitoring of an aircraft, while differentiating the novice ATCOs from expert and intermediates, not between experts and intermediates. Moreover, this signature is a good first step in quantifying the generic flight path monitoring behavior of ATCO, as it could also be further correlated with other cognitive measures, to better understand the monitoring

strategies of ATCOs. This could also be applied to different airspace sectors.

Alerts and aids could be directed on an aircraft flying with no change in FL for the purpose of maintaining the regular generic flight path monitoring behavior of ATCOs. Training programs could be more curated for prospective ATCOs, where a lesser focus on the generic flight path monitoring for intermediates is needed. A benchmark to differentiate the expertise level of the ATCOs in operations could be also created for their respective generic flight path monitoring behavior. Lastly, this signature could also pave the way for the representation of an operator's visual monitoring behavior in other surveillance domains, like vehicular operation and security surveillance.

ACKNOWLEDGMENT

The authors would like to acknowledge and thank the staff at Thales LAS France, Thales Solutions Singapore, and Air Traffic Management Research Institute of Nanyang Technological University, Singapore for their contributions and support toward this work. A patent has also been filed as part of this research.

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