Data visualization approaches in eye tracking to support the learning of air traffic control operations

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Due to the high cost of training new air traffic control specialists (ATCSs) and the expected increase of new hires in the near future, we need less costly methods to effectively train them. One of the approaches is to utilize expert ATCSs' visual scanning characteristics as a learning method; however, there are many issues that need to be addressed when we try to visualize and/or aggregate complex raw eye movement data (i.e. eye fixations, durations, and saccades) into meaningful patterns. In this paper, we provide a compact and conceptual review of how the eye movement data visualization methods have been evolving. In addition, we further explain the concepts of recently advancing data visualization approaches to analyze the eye movements of ATCSs in order to better evaluate human performance or train novices.

I. Introduction

Eye movement (EM) research, also known as eye tracking or gaze research, is an integral part of Human Factors and Human-Integrated System researches that investigate humans' visual perceptual behaviors and/or discover the causes for human errors in order to increase human and/or human-integrated system performances. The eye-mind hypothesis (Just and Carpenter, 1976) implies that our cognitive processes are highly correlated with our EMs, and in many cases, goal-oriented tasks induce overt orienting meaning that our attention process is a function that follows our eye fixations (Helmholtz, 1896; Johnson and Proctor, 2004). Furthermore, when performing time constrained tasks having specific objectives, we tend to selectively apply our visual attention to areas of interests (AOISs) which are highly associated with theories such as spotlight metaphor (Posner, Snyder, and Davidson, 1980) or zoom lens metaphor (Eriksen and St. James, 1986; Eriksen and Yeh, 1985).

In ATC operations in enroute, terminal, and tower environments, we perceive and interrogate most of the data and information through our vision; therefore, if we can better understand and visualize expert ATCSs' visual perceptual or visual scanning characteristics, then we might be able to use the findings to effectively teach the novices (e.g. FAA Academy trainees). Furthermore, the novices might be able to analyze their own EM characteristics to relate those characteristics with their performance and find ways to improve their performance.

In order to use the EM characteristics and/or patterns as a learning method, those who are not EM research experts such as ATCSs or trainees should be able to easily interpret the EM data visualization outputs. Specific to enroute ATC environment, There have been many researches to better understand the ATCSs visual perceptual behaviors or cognitive processes through interviews ore recalling procedures when detecting aircraft conflicts (Eyferth, Niessen, and Spaeth, 2003; Kang, Bass, and Lee, 2014; Neal and Kwantes, 2009; Niessen and Eyferth, 2001; Rantanen and Nunes, 2005; Remington et. al, 2000; Willems, Allen, and Stein, 1999); however, we have been lacking EM data visualization methods that can used to teach the novices. One recent approach uses the video recorded experts' visual scanpaths (i.e. time-ordered sequence of eye fixations and saccades) as a learning method (Kang and Landry, 2014); however, the video recordings do not necessarily provide characterized and easily interpretable EM data visualizations that can further facilitate learning.

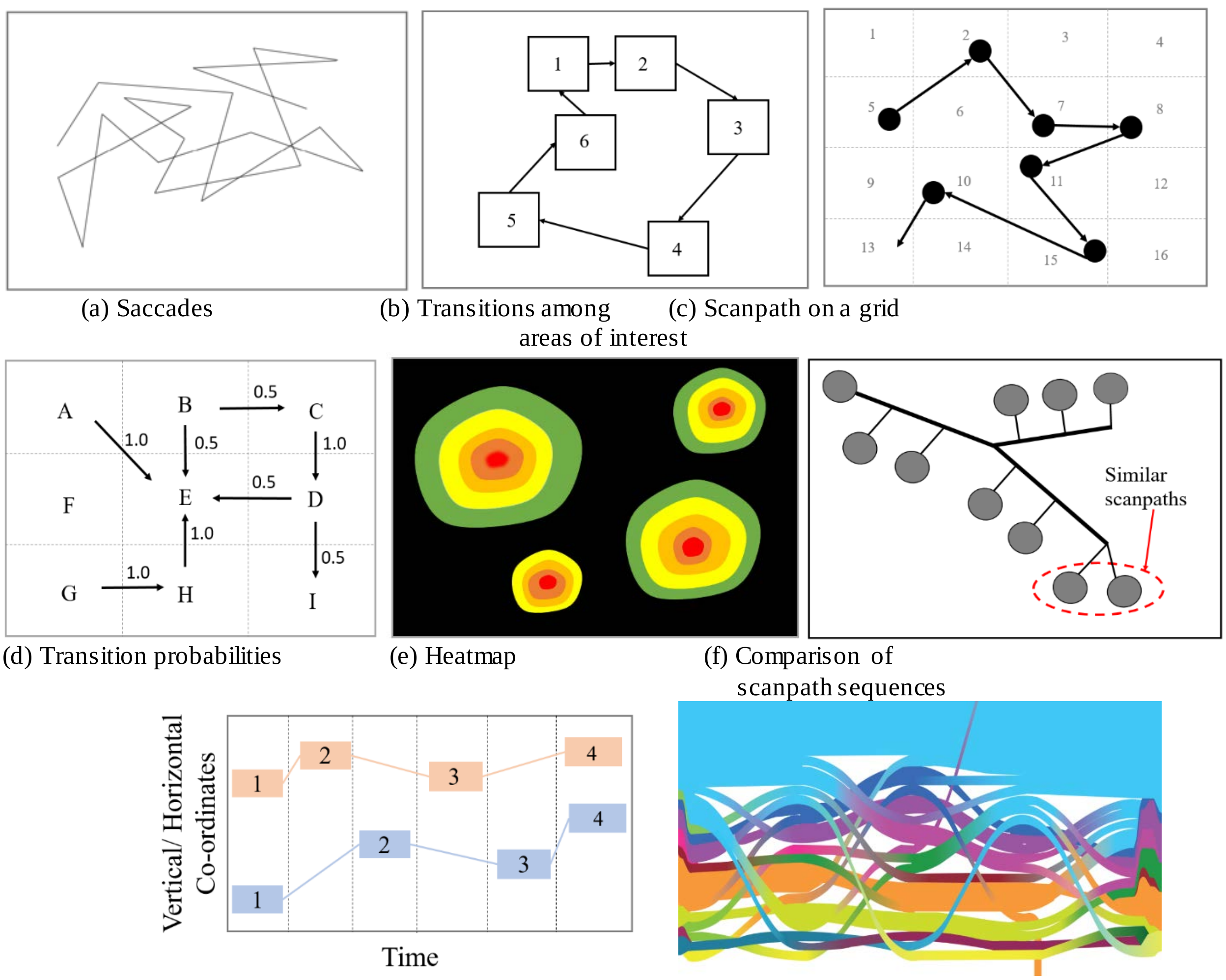
Therefore, in this paper, we introduce the evolution of some milestone EM data visualization approaches applied in various applications during the past decades in a chronological manner. Within those milestone researches, some data visualization approaches can be difficult to understand; therefore, we provide the visualization concepts into a much simpler and abstracted manner to facilitate understanding. After, we present several data visualization methods that are directly associated with enroute ATC, and how those methods can be effective on either analyzing visual perceptual/scanning characteristics and/or on evaluating human performance. Finally, we provide future directions of EM research in ATC operations.

II. Evolution of data visualization approaches: Summary through conceptual and abstracted representations

Figure 1 shows some of the important data visualization methods abstracted into simpler expressions. Figures 1(a) and 1(b) are based on the pioneering works of Yarbus (1967) and Noton and Stark (1967) who started to visualize the EM data collected from eye trackers; however, how they analyzed and visualized the data are very different since Figure 1(a) shows raw saccadic EMs of one participant whereas Figure 1(b) introduces areas of interests (i.e. boxed labeled with numbers and provides aggregated EM pattern obtained from multiple participants.

In more detail, Yarbus' (1967) research question was "how do we observe a picture when given different tasks?" Yarbus provided a picture with several persons greeting each other, then the participants were provided with seven types of tasks (e.g. "estimate the ages of each person" or "remember clothes worn by each person.") Yarbus illustrated the raw saccadic EMs of each output in the form provided in Figure 1(a), compared them through visual observations, and concluded that the EMs are idiosyncratic based on the given task.

On the other hand, the research question of Noton and Stark (1967) was "Can we discover a dominating visual scanning pattern from multiple participants when a picture of a face is observed?" To do so, Noton and Stark created the concept of areas of interest (AOI) that represents the elements within the picture such as nose, eyes, mouth. Then, the EM transition probabilities were calculated from one AOI to another AOI in order to identify a dominant EM pattern conceptually illustrated in Figure 1(b) which show that the majority of the participants observed the elements 1 through 6 following the sequences represented by arrows.



(a) Saccades (b) Transitions among areas of interest (c) Scanpath on a grid

(d) Transition probabilities (e) Heatmap (f) Comparison of scanpath sequences

(g) Time plot of areas of interest (h) AOI rivers

Figure 1. Simplistic representation of various eye movement data visualization approaches

The visualization of the EM data that most researchers apply today were formally defined by Goldberg & Kotval (1999) (Figure 1(c)). In Figure 1(c), we can see visual scanpath composed of eye fixations (i.e. black dots) and saccades (i.e. arrows). We say that an eye fixation occurred if a participant observes the same spatial location for a certain duration (e.g. 100ms). The details on how an eye fixation can be defined is provided in Kang (2017). In addition, Goldberg and Kotval divided the display into a gridded space (or AOI grids) so that all eye fixations occurred on the display can be mapped to an AOI.

Underwood et. al (2003) combined the AOI grid approach of Goldberg and Kotval (1999) and the transition probability approach of Noton and Stark (1967) to analyze how expert and novice drivers make different EM transitions from their driving field of view that was divided into eleven grids. Figure 1(d) shows one of the ways to visualize the transitions from one grid to another associated with the transition probabilities. For example, in Figure 1(d), an eye fixation starting at grid "B" has the probability of 0.5 to move to grid "C" and 0.5 to move to grid "E."

EM data provided eye fixation locations and saccades among the eye fixations to represent the visual scanpaths, but also provide the duration of each eye fixation. For example, an eye fixation on a spatial location can occur for 100ms or even much longer such as seconds or tens of seconds. Therefore, to illustrate how long certain locations are observed, the concept of heatmap was adopted (Caldara and Miellet, 2011; Reeder, Pirolli, and Card, 2011) (Figure 1(e)). The heatmap visualizes the extent of eye fixation duration occurring on various regions on the display using a color code (e.g. red means long eye fixation duration, yellow means moderate duration, and green means short duration).

Furthermore, the visual scanpaths can be expressed scanpath sequences. Assuming three AOIs are defines using enumerated types such as "A," "B," and "C," then if eye fixations occurred on "A," "B," "C," then back to "A" sequentially, then the resulting scanpath sequence is "ABCA." We can compare the a pair of sequences (e.g. "ABCBABACA…" and "CBABACBAC…") using the string edit algorithm that computes the similarity of enumerated sequences through the required number of edits (i.e. insertions, substitutions, and deletions) to transform one sequence to the other. This algorithm originated from comparing DNA sequences in Bioengineering, and Brandt & Stark (1997) applied the algorithm to compare the visual scanpath sequences. The comparison can be visualized at a tree diagram to align similar sequences closely (West et. al, 2006) (Figure 1 (f)).

More recently, researchers have been introducing methods to visualize the EM data by considering the time element often called timeline visualization. Grindinger, Duchowski, and Sawyer (2010) represented the time order in which various AOIs were fixated upon at different time instances (Figure 1(g)). Within the figure, the X-axis is the time and the Y-axis can indicate either the vertical or horizontal spatial coordinates. The Different colors can indicate either different individuals or groups, and the numbers indicate the order of eye fixations.

Another way to represent how the AOIs are visited based on time is to create an AOI river plot (Burch, Kull, and Weiskopf, 2013). The X-axis is the time and the Y-axis shows the bandwidth of the defined AOIs. In more detail, different AOIs as represented as different colors and the thickness of any river within the figure is proportional to the eye fixation numbers (or frequencies) aggregated among all the participants. If the river creates a few streams, it means that the some proportions of the total eye fixations have moved onto other AOIs. If the streams converge to a single river, then it means that the eye fixations on different AOIs have move onto a single AOI.

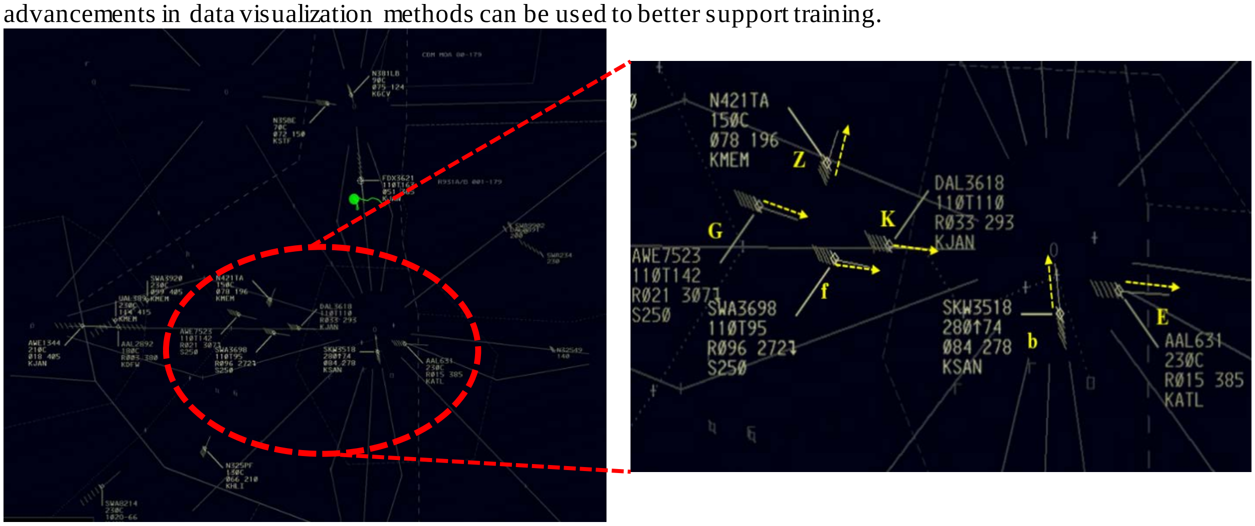
Although we have provided some important data visualization methods in a chronological and abstracted manner, there are various other visualization approaches in literature that we haven't described such as Dot-plot method (Goldberg & Helfman, 2010), ScanMatch algorithm (Cristino, Mathôt, Theeuwes, & Gilchrist, 2010) , MultiMatch method (Dewhurst et al., 2012) attention histogram method (Kurzhals, Heimerl, & Weiskopf, 2014), and node-link approach within time-to-space mapping (Burch, Beck, Raschke, Blascheck, & Weiskopf, 2014). These methods are either visualized based on statistical analysis methods or expands upon the visualization methods explained above.

III. Advancements of data visualization methods in air traffic control research

Although many plausible and insightful data visualization methods were explained, it is challenging to directly apply some of those methods in ATC tasks, especially in enroute aircraft conflict detection task. Specifically, some barriers are that the targets (i.e. multiple aircraft and their associated data blocks) move within the display, and there are no starting or ending points meaning that the ATCS or trainee can choose to start scanning the display from any part or aircraft within the display (Figure 2). Furthermore, when interrogating pairs or groups of aircraft to determine a conflict, back and forth eye movement transitions occur within those pairs or groups, and the transition (or saccadic) direction from one aircraft to another (e.g. first observing aircraft A followed B, or first observing aircraft B followed by A) wouldn't necessarily matter as long as we can find out that the visual interrogating among those pairs or groups are taking place.

Recent efforts include addressing the issues with dynamic moving targets by designing Targets of Interest (TOIs) or Dynamic Areas of Interest (DAOIs) around each aircraft and its data block instead of using spatially fixed AOIs (Kang and Landry, 2009; Kang and Bass, 2014), and furthermore developing an automated method to create those TOIs and DAOIs (Kang et. al, 2016).

In addition, recent efforts to address the other barriers include, but not limited to, investigating whether novices can learn from observing experts' visual scanpaths (i.e. time ordered sequence of eye fixations and saccades) (Kang and Landry, 2014), comparing experts' and novices' EM characteristics (Kang and Landry, 2015), classifying experts' initial global visual scanning patterns (McClung and Kang, 2016), providing time-frame based EM characteristics using the network theory (Mandal, Kang, and Millan, 2016). In this paper, we introduce how the recent advancements in data visualization methods can be used to better support training.



(a) **(b)**

Figure 2. Snapshot of a simulated DSR radar screen. (a) Snapshot of the total radar screen. (b) Detailed view of a small part of the screen showing the aircraft code names (characters in yellow) and their direction of movement (yellow dotted arrows) on the display.

Directed Weighted Network (DWN) method – The DWN method can be used to address the question of whether we can visualize the various eye movement characteristics into a single graph in order to identify to which aircraft were more attended. The DWM method stems from the graph theory, and we can use the method to better visualize the aggregated eye fixation number, durations, and transition characteristic together.

The main idea behind the DWN method is that an AOI fixation sequence can be transformed into a DAOI transition matrix, which in turn can be visualized as a directed weighted network (Figure 3). A typical network consists of nodes (or vertices) and edges (or links) joining them. In the DWN approach, the nodes represents the AOIs and the edges among them shows the amount of eye fixation transitions that occurred among.

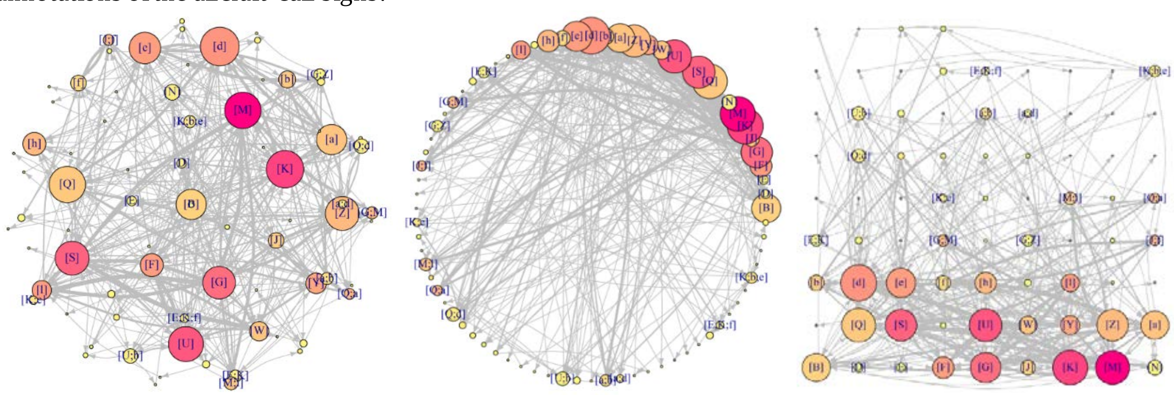
The various properties of the nodes and the edges are customized to visualize the different attributes of the eye fixation data. For example, the size of a node is made proportional to the number of eye fixation occurring on the corresponding AOI, the thickness of an edge (between any two nodes) is made proportional to the amount of saccadic movement happening between the corresponding AOIs in the direction shown by the edge direction, and lastly the color of the nodes are based on a heatmap where red means high and yellow means low eye fixation duration on the AOIs respectively.

(a) Sphere layout **(b) Circle layout** **(c) Grid layout**

Figure 3. Conceptual representation of the various layouts of the DWN visualization framework. (a) Sphere layout- nodes uniformly placed throughout the area of a circle (b) Circle layout – nodes placed on the circumference of a circle (c) Grid layout – nodes places on a 2D rectangular grid structure

In more detail, Figure 3 represents simple conceptual representation of the three layouts pertainign to the DWN framework of AOI fixaiton visualisaiton. The three layouts represented are namely sphere, circle and grid layout. The *Sphere layout* (Figure 3(a)) puts the nodes of the network representation on the surface of a sphere. For the present 2D case, the sphere is a circle and the surface area is shown by the area inscribed by the circular boundary. The nodes are places uniformly on the inscribed area of the circle. The *Circle layout* (Figure 3(b)) is used to place the nodes of the network around the boundary of a circle so that we can better see characteristics of the transitions. The placement of the nodes can be changed using a different ordering of their names. The *Grid layout* arrange the nodes in a rectangular grid. The two parameters of the grid layout are the width and the height of the grid, and the relative position of the nodes in the grid layout can be changes by using a different ordering scheme of the nodes.

Examples on how the DWN can be visualized in an enroute conflict detection task is provided in Figure 4 which shows the important aircraft observed (through visualizing both the frequencies and durations represented by the circle size and circle color respectively) and the amount of complex EM transitions (or saccades) over a 20 minute period when detecting conflicts from a scenario example shown in Figure 2. The letters within the circles are annotations of the aircraft call signs.



(a) **(b)** **(c)**

Figure 4. DWN visualization examples following (a) Sphere layout (b) Circle layout and (c) Grid layout.

It is noted that the examples provided in Figure 4 show complexity due to the amount of EM data accumulated over the 20 minute period. When the trainees want to see their EM characteristics after performing a conflict detection task, we can first show them the overall DWN visualization, then break it down by shorter time-frames or based on events (e.g. introduction of a new aircraft within a sector) so that the scale of the DWN network becomes smaller and the trainees can better understand how their visual attention has been shifting based on the shorter time-frames or events.

Initial Global Scanpath (IGS) approach – The IGS approach can be used to discover and classify the visual scanning strategies used either by the expert ATCSs or trainees. One of the main ideas of this approach is to map the verbal or written descriptions of the experts' strategies with the obtained EM data. For example, expert ATCSs provided answers that they would apply visual scanning strategies such as circular, linear, zig-zag, augmented, and/or proximity-based strategies (Kang, Bass, and Lee, 2014; Kang and Landry, 2014). The answered visual scanning strategies can be mapped to the experts' EM data to validate their strategies, and furthermore discover certain strategies that the experts did not articulate.

The conceptual representation of the visual scanning patterns are provided in Figures 5 and 6. Although it is easy to verbally say "circular," it is often difficult to mathematically define a circular scanpath pattern; however, as long as we have enough number of eye fixations on multiple targets (e.g. multiple aircraft and their data blocks), we can deduct the circular patterns through developing algorithms. The classification of a "linear" scanpath is even more challenging, since our EMs do not necessary move a straight line, but gradually moves from one end to another end within the display while making more of a zig-zag EM to visit the surrounding aircraft. Similarly it is difficult to classifying other verbally spoken strategies as it requires mathematical algorithms to represent the spoken strategies. Furthermore, the visual scanning strategies are affected by the layout of the targets on the display. If the targets are not uniformly distributed within the display, then we might not obtain the anticipated scanning patterns.

Examples on how the visual scanning patterns are be visually represented in an enroute conflict detection task is provided in Figure 7. The actual EM data obtained from the expert ATCSs are much more noisy since they not only perform global scanning but also immediately make back and forth EMs when possible conflicts are detected. However, through filtering out the data multiple times, we are able to produce much clearer scanning patterns as provided in Figure 7. The IGS method results can be used to show the experts' visual scanning patterns to the trainees as a learning method or to show the trainees their own visual scanning patterns so that they can realize and adapt their own scanning behaviors based on their needs.

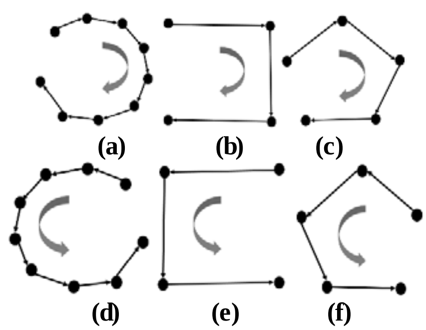


Figure 5. Various representations of circular scanpaths that can be either clockwise or counter-clockwise.

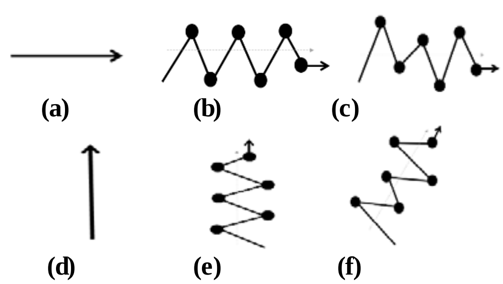
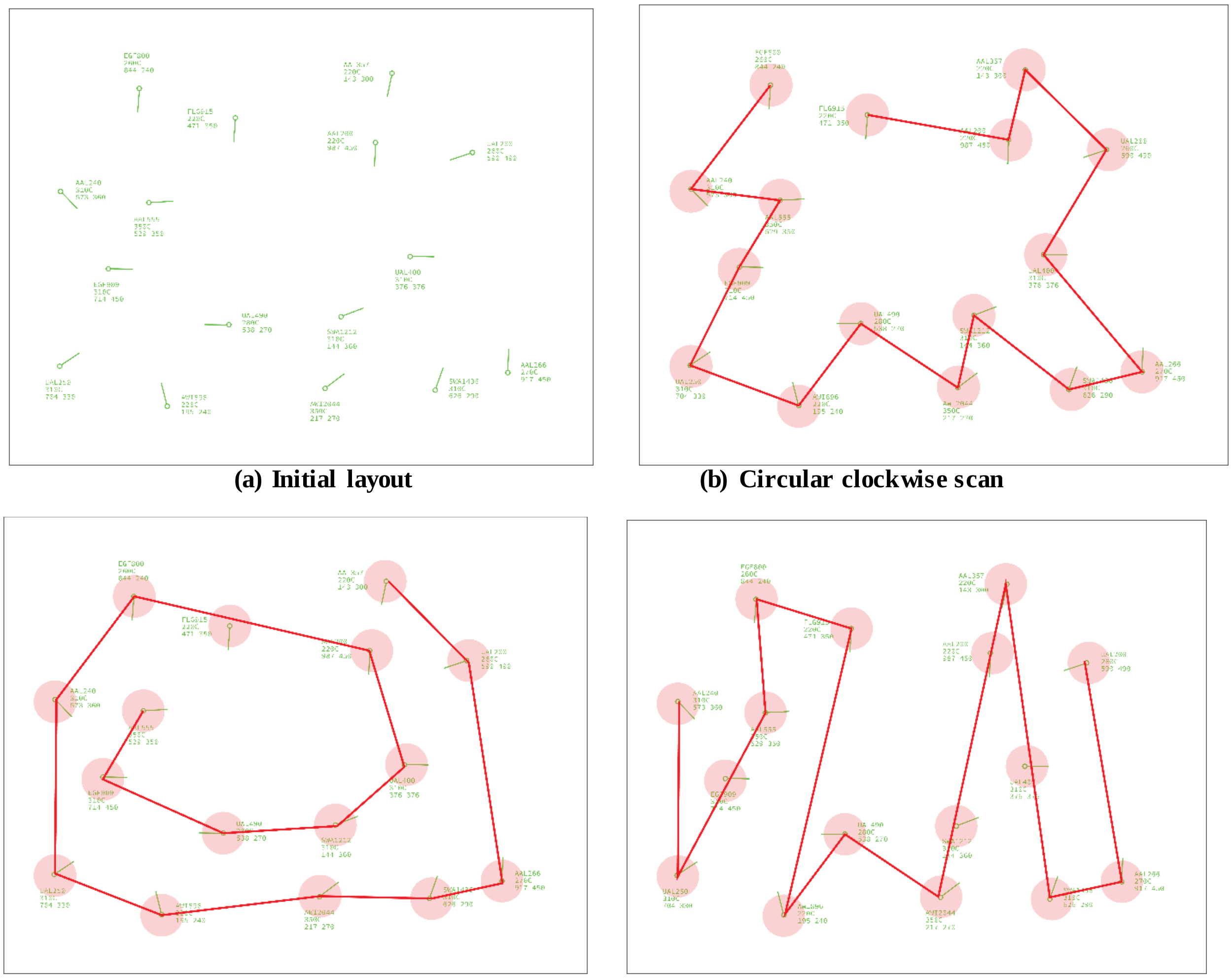


Figure 6. Various representation linear scanpaths that can be horizontal, vertical, or diagonal.



(a) Initial layout **(b) Circular clockwise scan**

(c) Circular spiral scan **(d) Linear zig-zag scan**

Figure 7. IGS method examples. (a) shows an example of initial aircraft layout on a radar display.

Visual Grouping (VG) method – The VG method is used to discover which pair or groups of targets (e.g. aircraft) were interrogated that would enable us to evaluate performance (e.g. whether the conflict pairs of groups were interrogated). The IGS method investigates the global scanning strategies leaving out the back and forth interrogation of pairs or groups that might have conflicts, whereas the VG method concentrates more on the which pairs or groups were interrogated once possible near future conflicts are identified.

The VG method is also called the maximum transition-based agglomerative hierarchical clustering method (MTAHC). The underlying algorithm is to compute an unordered transition matrix (since the directions during the interrogations between or among the aircraft do not necessarily matter), then adapt the clustering method to hierarchically group the targets based on those pairs or groups that have more back and forth movements compared to other pairs or groups.

The conceptual representation of the VGs are provided in Figure 8. The VGs can form based on convergence, proximity, or spatial areas (e.g. left upper side or lower side of the display); however, in aircraft conflict detection task, it was shown that the experts tended to form VGs based on similar altitudes accompanied by conversions, whereas the beginners tended to form VGs based on only convergence rather than considering the altitudes first (Kang and Landry, 2015). Therefore, significant VG differences were found between the expert ATCSs and the beginners which were correlated with their performance.

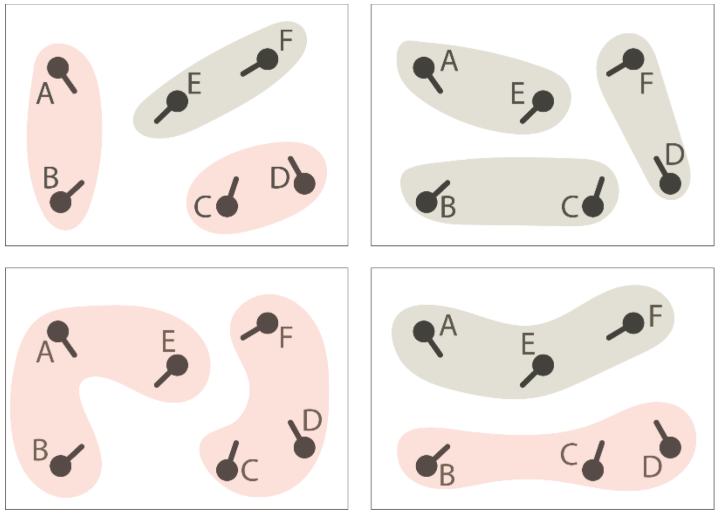
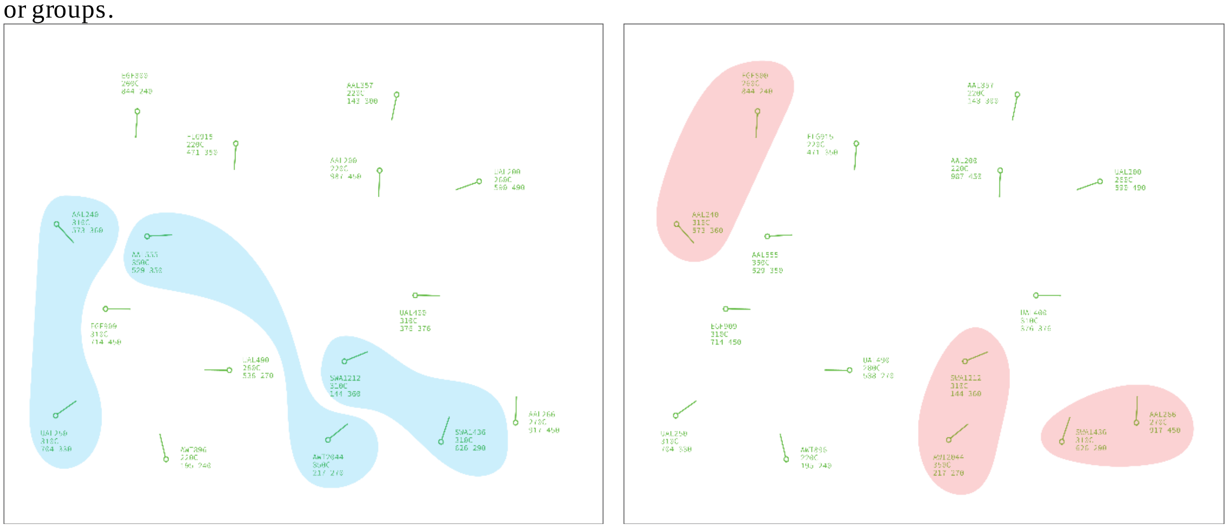


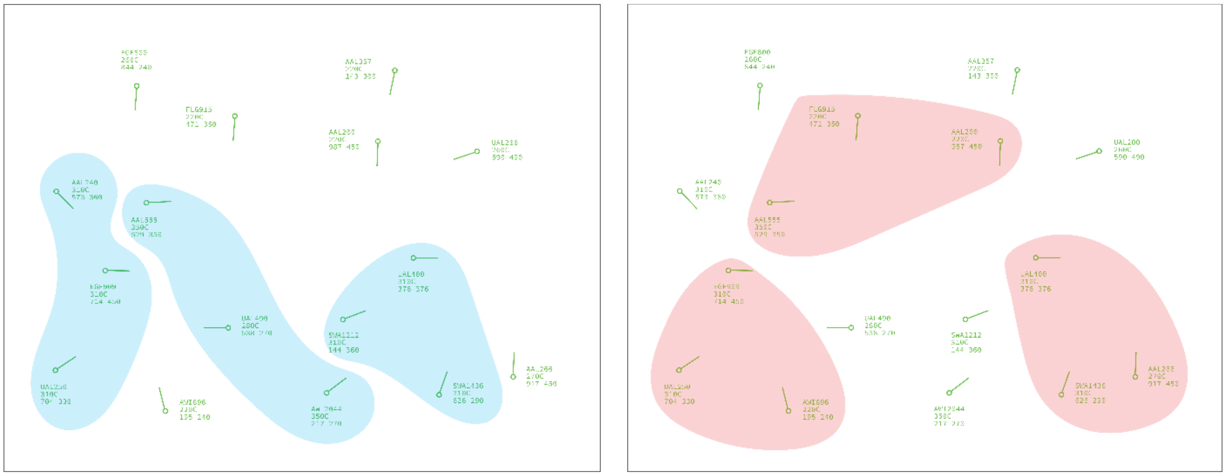
Figure 8. Conceptual representations of visual groupings (VGs): For a conflict detection task, interrogated aircraft can be grouped as a pair or a group. The VGs that does not contain conflicts can be additionally highlighted using a different color (e.g red).

Simplified examples of the how VGs form during a conflict detection task is provided in Figure 9. In Figure 9, there are three conflict pairs which are equivalent to the paired with the blue VGs in Figure 9 (a). Figure 9 (a) indicates that all conflicts were interrogated, whereas Figure 9(b) indicates that VGs were created around the pairs that will not have any conflicts in the near future. Figure 9(c) show the higher level clustering results with three aircraft that still include the conflict pairs, whereas Figure 9(d) does not.

Through the VG method, we can discover which pairs or groups of aircraft were interrogated by the experts in order to better understand their cognitive processes during the interrogations. In terms of trainees, we can identify the interrogated pairs or groups that that do not have conflicts. Then, the trainees would be able to delve deeper into finding out why they were too much focused on non-conflict pairs or groups and missed identifying the conflict pairs or groups.



(a) **(b)**



(c) **(d)**

Figure 9. Example of paired VGs ((a) and(b)) and grouped VGs ((a) and (c)). The MTAHC method enables us to first cluster pairs, then include other lesser interrogated aircraft to create larger clusters. In the above example, blue VGs indicates that there are conflicts within those blue VGs, whereas red VGs indicate that there are no conflicts within those red VGs.

IV. Conclusion and future research directions

In this paper, we provided the various data visualization methods that have been developed over the decades, and how those methods were improved to provide advanced data visualization methods that can be useful to the Aviation community. The conceptualizations and examples were simplified as much as possible to facilitate the understanding and promote interest to the Aviation community. In addition, we have shown that EM data can provide rich information and can support answering important questions such as which aircraft were most attended, what are the global (or general) visual scanning strategies, and which aircraft pair or groups were interrogated in order to better understand the visual perceptual behaviors and/or evaluate human performance. However, there are many more researches required to better support the overall training within the Aviation community.

First, we can expand the application areas to tower control and other technical operations. The capabilities of EM research are not limited to the enroute environment, and can expand to investigate the visual scanning strategies of Tower controllers, aircraft inspectors, or other technical operators through identifying appropriate methods for each type of task or objectives. Second, many data visualization methods require much effort by the analysts, and we need to develop an automated software so that the data can be visualized quickly for effective use. An integrated and automated data visualization capability tailored to the Aviation community that do not need to rely on limited capabilities of commercial eye tracking analysis software is much needed. Third, the ATCSs and trainees should be able to easily access the various data visualization features and interpret the outputs. To do so, we need to develop user-centered interfaces and provide contextual information regarding the data visualizations to facilitate the learning of the trainees. Finally, visualized EM data should not be accessible only after the task has been complete, but also during the task. Real time analysis will enable us to support on the spot alerting mechanisms and real time feedback to the trainees.

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