Visual Conspicuity Measurements of Approaching and Departing Civil Airplanes using Lab Simulations

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***Abstract* — Safety operations of airports and en-route aircraft are still one of the main issues in air traffic management (ATM). Even though technology is already advanced enough to display simulated aircraft on the computer, airport tower controllers still need a clear vison of the approaching and departure aircraft in order to observe the status of aircraft and respond quickly in case of emergency. Conducting field tests in the airport may be restricted by the schedules of the airport operation and can even interfere with the tasks of tower controllers. As a result, it is costly and time consuming to conduct field visual conspicuity tests in the airport. On the contrary, lab simulations can create as many scenarios as possible and are easy to prepare. If the lab simulation produces a good fidelity and accuracy rate, it can replace the field test and turn conspicuity measurements to be more flexible and convenient. The aim of our experiments is to find the relations between visual conspicuity and different visual parameters. Based on our experiments, we can help the tower controllers to better detect and monitor the plane status in the airport vicinity. This can benefit the safety operation of the airport and contribute to more efficient ATM as well.**

Keywords - Visual Conspicuity, Airplane landing and departure, Lab Simulation, Solidworks Model, Air Traffic Management

I. INTRODUCTION

The visual conspicuity for the approaching planes in the vicinity of the airport is very important for the tower controller to track the real status of the airplanes. But measuring the visual conspicuity in the control tower takes a lot of man power and time; and also it may be under the restriction of the schedules of the planes. Most importantly it could interfere with the work of controllers. If simulations in the lab can maintain certain fidelity, we can perform lab simulations instead of the real scene measurement, which can save time and costs. At the end, the experiment results of visual conspicuity in the lab simulations are compared with the field test results to prove our lab simulation effectiveness and fidelity.

In 1995, Radio Technical Commission for Aeronautics came up with free flight [1] concepts for the first time. Free flight means pilots should have more responsibility for the separation of en route aircraft. Thus air traffic controllers (ATCs) can reduce their work load and focus more on increasing the efficiency and capability of the airspace. But if emergency takes place, ATCs should concentrate on helping the aircraft solve conflicts and reduce accidents happening. Aircraft crews and ATCs must interact with each other and monitor any changes or conflicts in the airspace [2] to ensure the safety operation. Aircraft departure and approaching are the most crucial stages among the entire route. Many accidents happened during departure and approaching processes. Therefore, how to improve the safe aircraft landing and departure is one of the main research topics for ATM. ATCs need a clear vison of the departure and landing aircraft to monitor the aircraft status. Visual conspicuity is one of the areas that can improve the safety standard around the airport.

A lot of visual conspicuity research has been done so far. For example, Toet et al. used graphic slides of the scene photos with military vehicles for the subject to undertake measurements of visual conspicuity in lab conditions [3]. Visual conspicuity is defined by the peripheral area between the object and the observer eye fixation where the object is being distinguished at first time by the observer. The visual conspicuity tests were conducted by two authors and the visual search performance tests were done by 64 subjects. The results demonstrate that mean search time and the logarithmic values of visual conspicuity have a linear relation with each other. Also the target visual conspicuity lab test agrees with the field tests.

Bok et al. [4] used a projector with a plane model to quantify the visibility for subjects. They used ANOVA methods to control the visual parameters of the plane model and background so that the effect of different parameters on the visual conspicuity can be extracted. Then based on the results, their team established a mathematical model for the Detection Radius as a function of target size, lightness and chromaticity.

The relation between the cumulative probability of target discovery and the relevant visual conspicuity area has been experimentally revealed. Visual conspicuity area stands for the visual field area where an object is firstly detected after a single eye fixation. Based on the experiment, Engel [5] has found non-targets can be discovered spontaneously during the experiment and are proportional to the corresponding conspicuity area. However, instructions to the subjects on prohibiting the non-targets fixation can lead to the reduction of the effective size of the conspicuity area.

Engel [6] also found that eye fluctuations may happen in the target spotted direction during the conspicuity experiment. Spontaneous appearance of eye fluctuation is related to the visual conspicuity area and target eccentricity. His research results illustrate the importance of the visual conspicuity area in visual target detection.

Andrew et al. [7] proposed a Spatial Standard Observer (SSO) method to easily calculate the visibility threshold range for many conditions. Then the authors compared measuring results of the visibility of aircraft images predicted by SSO with the results obtained by human observers in order to tune the calculation accuracy. But the limitations are: firstly, the measurement and prediction of visibility of aircraft are based on patterned backgrounds. Secondly, the authors only analyzed and predicted thresholds for photopic vision only. The results show that SSO can calculate over any distribution of desired parameters, and can do so without the effort and expense of field tests.

Chaudhuri et al. [8] used a multi-layer perceptron method to predict the visibility of the airport during fog. They found that the visibility was related to several surface parameters, including surface temperature, pressure, wind direction, humidity etc. As a result, they can predict the visibility based on the pre observation in the airport vicinity. This kind of method can be also used by us to predict the visibility of the airplane by taking into account of several parameters, which are linked to the changing of the visibility. The overall goal is to predict the airplane visibility in a precise manner so as to increase the safety operation of the airport. Increased airplane visibility will also enhance the possibility for collision avoidance [9] and thus the safety operations.

The aim of our research is to establish a mathematical model to define the relation between the visual parameters and the visual conspicuity. The parameters include chromaticity, lightness, object size (distance), contrast and observing angle. Moreover, the relation between visual conspicuity and search time is also demonstrated in this study.

Figure 1. Airbus A320 simulation model.

Figure 2. Departing and Approaching.

II. METHODOLOGY

We draw civil aircraft Airbus A320 and Boeing 737-800 using SolidWorks as the plane models for conspicuity measurements. Then we can fine tune the visual parameters to get the exact images we want. The dimension of the image is 1379x698. The location of the plane model on the image should be settled, that is to say on the top right corner of the image for variable control. Two planes are all in white color. The background is the real image of a sunny sky with clouds to make the scene look real. The background photo and a plane simulation example can be seen in Fig. 1. After the preparation, 32 subjects aged from 17 to 25 with normal eyesight are required to stand in front of the screen to detect the plane conspicuity. After all subjects finish the experiments, except the low-quality data, all the rest of data will be processed and the mathematical model will be established based on the data acquired.

Content below shows effects of changing different parameters.

–A. Approaching or Departing

The flight posture will change depending on whether the plane is approaching or departing if we assume the observation point remains the same. The flight posture will have an effect on the visual conspicuity of the plane. As can be seen in Fig. 2, the two images show the posture for departure and approaching respectively. We can see there is a clear difference between the two states.

–B. Chromatics

In the CIElab color space [10], Chromatics consist of two independent parameters. One is hue, which is an angular component. The other is chroma, which is a radial component. Equation (1) describes Chroma and Hue calculation methods [11].

$$\begin{gathered} Chroma = \sqrt{a_*^{\,2} + b_*^{\,2}} \\ Hue = \tan^{-1}(\frac{b_*}{a_*}) \end{gathered} \quad . \tag{1}$$

In (1), a_* stands for the red/green axis. The axis is the red axis when $a_* < 0$ and the green axis when $a_* > 0$; b_* represents the blue/yellow axis. If $b_* < 0$, it is the blue axis and if $b_* > 0$, it is the yellow axis. The range of the changing Hue is from -180° to $+180^\circ$. The hue adjustment results can be seen in Fig. 3.

Figure 3. Hue changing from -180° to $+180^\circ$.

Figure 4. Lightness changing from -140L to 80L.

Figure 5. Contrast changing.

–C. Lightness

Lightness may differ if the weather in a real situation changes. Lightness is also one of the key elements for the visual conspicuity measurement. The interval we use is 10L and we start from -140L to 80L. The images with different lightness are displayed in Fig. 4. They change from the lowest -140L to the highest 80L.

–D. Contrast

Contrast is not only determined by brightness but also color. Scientific research shows that human eyes are more sensitive to contrast than the absolute luminance [12]. Here we define our contrast as luminance contrast. The equation can be seen in Eq. 2 [13]. The images with different contrast have different visual effects on the observers. The contrast changing result can be seen in Fig. 5.

Figure 6. Distance changing.

$$\frac{I_o - I_b}{I_b} \tag{2}$$

I_o and I_b represent the luminance of the object and the background, respectively.

–E. Distance

Distance will affect the size of the plane on the display image. A larger distance will decrease the visual conspicuity significantly. As shown in Fig. 6, a larger distance means a smaller size of the plane on the image. Moreover, the reaction time for the identification of the plane will also go up.

III. RESULTS ANALYSIS AND DISCUSSION

–A. Results for departure conspicuity vs search time

After getting all the simulation data from experiments, we input the departure conspicuity detection time data into MATLAB. We can use MATLAB to generate the curve for comparison. The graph generated by MATLAB can be found in Fig. 7. The searching time plunges very significantly when the airplane is least conspicuous, or out of the human detection range. The curve flattens after the plane is already conspicuous enough for searching. The search time consists of observer reaction time and plane searching time. After the plane is obvious enough, the plane searching time will decrease to a small value which can be neglected when compared to reaction time. As a result, the curve becomes stable.

–B. Results for approaching conspicuity vs search time

We also input the data into MATLAB to generate the graph of approaching conspicuity vs search time. In Fig. 8, the curve drops significantly with the increase of the conspicuity. From conspicuity of 30, the curve becomes stable. But the peak at conspicuity 140 probably occurs because of the plane hidden behind the clouds even through the plane is big enough for identification. When we compare Fig. 7 and Fig. 8, approaching search time is larger than landing search time at first. But then both become flat at around the same search time value. We can also understand that there is a clear difference between the landing and departure conspicuity detection time.

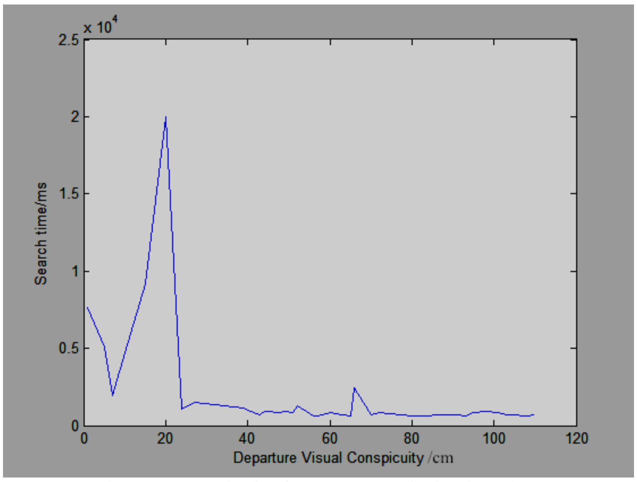

Figure 7. Results for departure conspicuity detection.

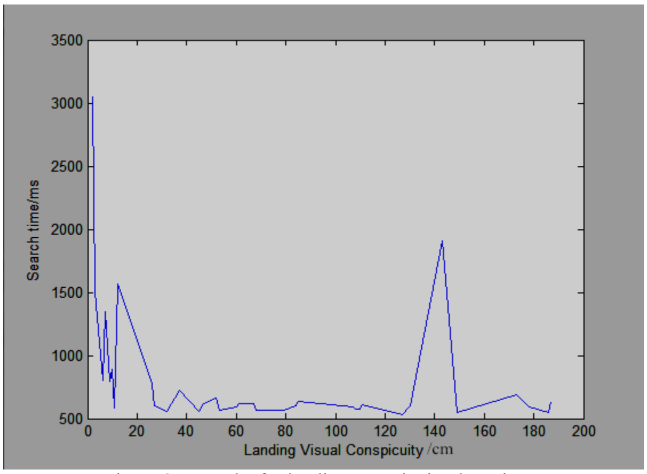

Figure 8. Results for landing conspicuity detection.

It is because that the orientation of the planes results in the difference of effective observing size. But overall the curve becomes horizontal when the plane comes near to the observer.

–C. Results for visual onspicuity vs distance

As we can see in Fig. 9, the conspicuity goes up with the increase of the plane observing size on image, which means the further the distance, the smaller the conspicuity. The lower curve is the identification conspicuity and is clearly smaller than the detection conspicuity. It is because the conspicuity area should be smaller so that observers can identify the characteristic of the object. Also it takes more time to identify the object. The identification conspicuity and the detection conspicuity are both quadratic equations. Moreover, we can see that when the observing size is near 140mm, the detection conspicuity drops. It is because the screen is no more big enough for detection of the large plane.

So the data beyond 140mm should be ignored.

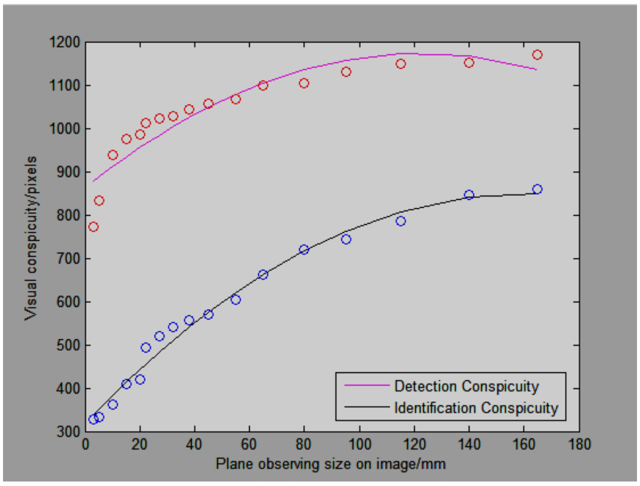

Figure 9. Results for conspicuity vs distance.

The fitting equations for the detection and identification conspicuity are shown in Eq. 3.

$$y_{detction} = -0.0205x^2 + 5.0453x + 862.7387$$
$$y_{identification} = -0.0207x^2 + 6.6182x + 319.3139 \quad (3)$$

–D. Contrast

Fig. 10 demonstrates that the detection conspicuity curve fluctuates at the contrast between -50% and -20% and gets to the highest point when contrast is -10%. After that, the curve plunges rapidly until contrast is 20%, where the detection conspicuity begins to decrease slowly. The identification curve declines slowly except that there is a small peak at contrast of 22%. From the results, -10% contrast is the most suitable and obvious for observer to detect airplane.

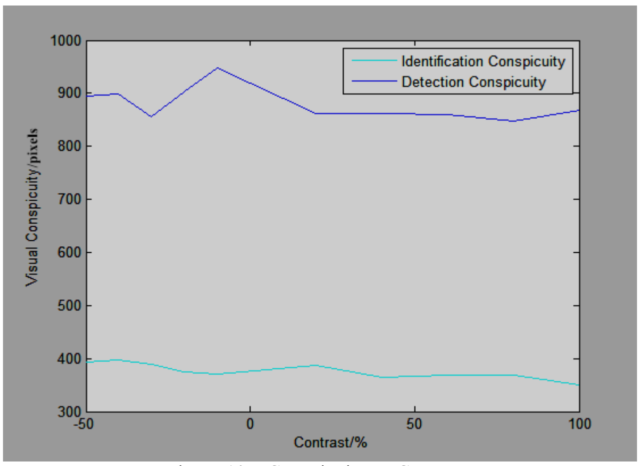

Figure 10. Conspicuity vs Contrast.

While -50% contrast has the largest identification conspicuity. Also, the detection conspicuity is always larger than the identification conspicuity, and detection conspicuity fluctuates more violently than the identification conspicuity.

$$y_{detction} = -0.0003x^2 - 0.2959x + 885.4298$$
$$y_{identification} = 0.0001x^2 - 0.2416x + 379.927 \quad (4)$$

–E. Brightness

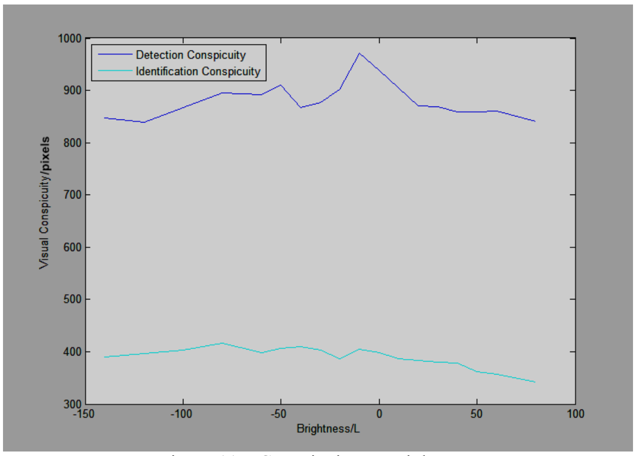

Figure 11. Conspicuity vs Brightness.

The conspicuity vs brightness curve starts to increase from the beginning until it reaches the top at brightness of -8L as shown in Fig. 11. Then it begins to drop. The most conspicuous point for airplane detection is when brightness is equal to -8L. The identification graph also has one peak which is at brightness of -80L. Therefore, the brightness does have an effect on the visual conspicuity, but the environment too dark or too bright can limit the visibility of the airplane.

The fitting equation for the detection and identification conspicuity can be seen in Eq. 5.

$$y_{detction} = -0.006x^2 - 0.3414x + 899.7249$$
$$y_{identification} = -0.003x^2 - 0.3993x + 399.7007 \quad (5)$$

We can see from the graph that the visual conspicuity measurement is in pixels, not in cm. The relationship between conspicuity in pixels and in cm are shown in Eq. 6.

$$y_{cm} = 0.1523 y_{pixel} \quad (6)$$

–F. Chromatics

From Fig. 12, we can see the detection conspicuity reaches a peak when the color is light green, and drops to the lowest as the hue increases to around 30%, which is blue. Then the curve becomes flat until it reaches another peak at hue of 150%, when the color is purple. For the identification conspicuity, the curve has a highest point at hue of -80%, which is dark green. After that, the curve becomes stable. The hue changes between -50% and 80% do not affect the identification conspicuity much. Since then, the identification conspicuity drops to the bottom at hue of 100%. Then the line goes up again and reaches another peak at hue of 150%. In conclusion, hue has different effects on detection and identification visual conspicuity. When the background is light green, it is easiest for the observer to detect the plane in the sky. But for the identification conspicuity, the value does not change so much in a large hue range, and dark green is the easiest color for identifying planes. It is hardest for observers to both detect and identify the plane in an orange color sky.

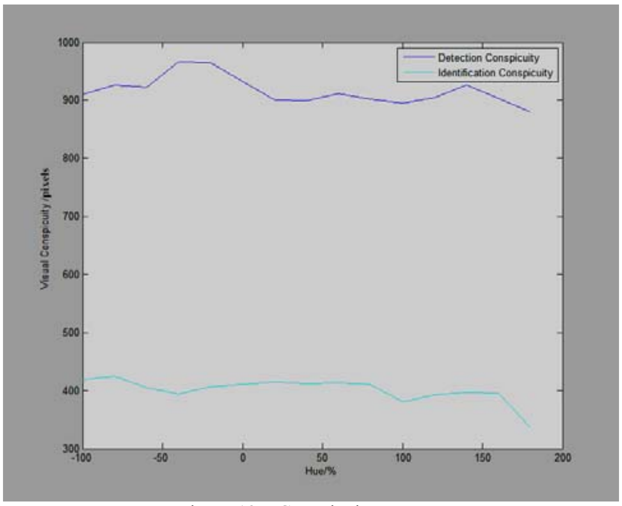

Figure 12. Conspicuity vs Hue.

IV. CONCLUSION

Our approach measures the relations between visual conspicuity and different parameters, including distance, chromatics, brightness, contrast and flight posture. Moreover, we found the difference between landing and departure visual conspicuity by checking the average search time of the plane. The curve clearly demonstrates that the search time drops when the visual conspicuity increases. Based on our results, we can think of methods to increase the visual conspicuity both for the approaching and departure aircraft by tuning the parameters until the visibility reaches the largest value. Also, each visual parameter has an obvious different effect on detection and identification conspicuity. As a result, actual field tests can be replaced by simulations in the lab if the lab simulation efficiency and accuracy has been proved. This can lead to a cost and time efficient visual conspicuity measurement which may help controllers to have better vison of the aircraft in the airport vicinity. This can not only meet the ATM demand of increasing safety operations of the airport, but also contribute to shape a future airport with more capacities and efficiency.

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