

Research on Visual Sense of the Officer On Watch

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Abstract - According to the COLREGs, every Officer On Watch (OOW) shall at all times maintain a proper look-out. Among all the available means of look-out, sight is the most basic and commonly used one. OOWs always need to make a full appraisal of the situation and of the risk of collision by sight, including estimating the range and bearing. Unlike the ranging equipment (such as Radar), OOWs, who are keeping a look-out by sight, cannot estimate the distance precisely according to their visual sense. In this paper, an experiment is carried out for finding the difference between the actual distance and the estimating one by OOWs with different onboard experience. The data are analyzed by using methods of statistics, Anomaly Detection, and Two-Step clustering for researching the human element of the visual sense during look-out. The factors, which can affect the visual sense, are revealed. Conclusions are drawn for improving the look-out and enhancing the safety of the navigation.

Keywords: Visual Sense, Officer On Watch, Anomaly Detection, Two-Step clustering, Human Element

1. INTRODUCTION

According to the COLREGs (*Convention on the International Regulations for Preventing Collisions at Sea, 1972*), "Every vessel shall at all times maintain a proper look-out by sight and hearing as well as by all available means appropriate in the prevailing circumstances and conditions so as to make a full appraisal of the situation and of the risk of collision."^[1] Therefore, visual observation is one of the most basic and important look-out methods. By using of which, range and bearing can be estimated. However, unlike the ranging equipment, such as Radar, distance feeling of human through the eyes is normally not accurate. So an experiment is designed to test the human element of the visual sense by comparing the difference between the actual distance and the estimating one.

2. DISTANCE MEASUREMENT EXPERIMENT

2.1 Basic Information

- **Time:** June 9, 2010;
- **Place:** 34°43'07"N, 135°17'28"E, Kobe University;
- **Visibility:** Good (10 n miles);
- **Tools:** Rangefinder, Eyes, Record Table;
- **Participants:** Class 1 Pilot Candidate (over 15 years' onboard experience), Class 3 Pilot Candidate (1-3 years' onboard experience), Master/Doctoral Student (no onboard experience).

2.2 Procedure

- Choosing 9 visible objects with different distances, heights, and backgrounds;
- Estimating distance with eyes by each participant, recording the distance of estimation on the table;
- Measuring distance with Rangefinder^[2], recording the actual distance on the table;
- Comparing the difference between estimating and actual distance, and discussing the reasons.

2.3 RESULTS

The values of estimating and actual distance are shown in Table 1.

Table 1 Estimating and Actual Distance (m)

Participant	Object								
	1	2	3	4	5	6	7	8	9
Class 1 Pilot Candidate 1	450	150	500	70	170	800	600	120	15
Class 1 Pilot Candidate 2	385	110	335	48	145	650	650	140	40
Class 1 Pilot Candidate 3	980	140	450	180	100	1000	500	190	45
Class 1 Pilot Candidate 4	450	135	450	72	145	620	1400	120	13
Class 1 Pilot Candidate 5	400	120	450	45	150	750	1000	150	20
Class 1 Pilot Candidate 6	1200	100	450	70	160	600	1700	135	25
Class 1 Pilot Candidate 7	800	100	300	35	120	650	1000	120	20
Class 1 Pilot Candidate 8	500	180	600	45	130	1200	1000	120	28
Class 1 Pilot Candidate 9	300	100	450	50	180	700	700	150	30
Class 3 Pilot Candidate 1	1300	80	350	50	130	300	800	120	25
Class 3 Pilot Candidate 2	500	120	280	110	120	800	1000	150	15
Class 3 Pilot Candidate 3	700	75	360	70	130	450	850	200	23
Class 3 Pilot Candidate 4	380	80	450	100	180	600	800	150	15
Class 3 Pilot Candidate 5	370	90	360	45	170	510	1500	120	27
Class 3 Pilot Candidate 6	450	70	300	80	130	600	650	160	40
M/D Student 1	550	87	280	70	230	720	340	157	25
M/D Student 2	200	100	200	30	130	600	900	200	30
M/D Student 3	500	100	300	100	150	400	900	200	30
M/D Student 4	300	100	400	80	150	620	600	120	33
M/D Student 5	300	130	320	110	120	600	615	130	50
Actual Distance	281	107	523	58	248	595	981	172	35

3. STATISTICS ANALYSIS

3.1 Average Value

The values of average estimating distance and actual distance are shown in Table 2.

3.2 Standard Deviation

Standard deviation is a widely used measurement of variability or diversity used in statistics and probability theory. It shows how much variation or "dispersion" there is from the average. A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data are spread out over a large range of values^[3]. The values of Standard Deviation are shown in Table 3.

Table 2 Average Estimating Distance and Actual Distance (m)

Participant	Object								
	1	2	3	4	5	6	7	8	9
All	551	108	379	73	147	659	875	148	27
Class 1 Pilot Candidate	607	126	443	68	144	774	950	138	26
Class 3 Pilot Candidate	617	86	350	76	143	543	933	150	24
M/D Student	370	103	300	78	156	588	671	161	34
Actual Distance	281	107	523	58	248	595	981	172	35

Table 3 Standard Deviation

Participant	Object								
	1	2	3	4	5	6	7	8	9
All	300	28	95	35	29	198	340	29	10
Class 1 Pilot Candidate	311	28	87	44	25	201	395	23	11
Class 3 Pilot Candidate	356	18	59	26	25	168	299	30	9
M/D Student	148	16	72	31	43	116	236	38	10
Actual Distance	281	107	523	58	248	595	981	172	35

3.3 Error Rate Distribution

The Error Rate can be calculated as the following formula:

$$\text{Error Rate} = (\text{Estimating Distance} - \text{Actual Distance}) / \text{Actual Distance} \%$$

3.3.1 Error Rate Distribution by Object Order

The Error Rate Distribution of all participants, Class 1 Pilot Candidates, Class 3 Pilot Candidates, and Master/Doctoral Students by object order are shown in Figure 1-4.

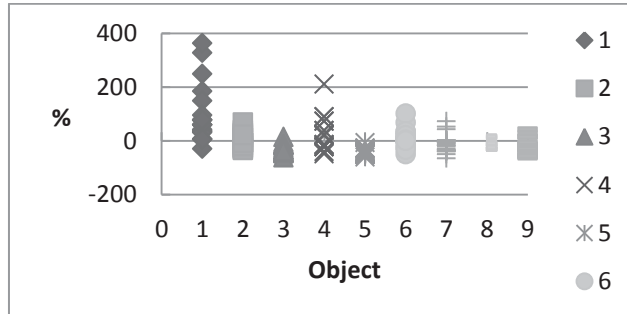


Figure 1 Error Rate Distribution of all participants (by object order)

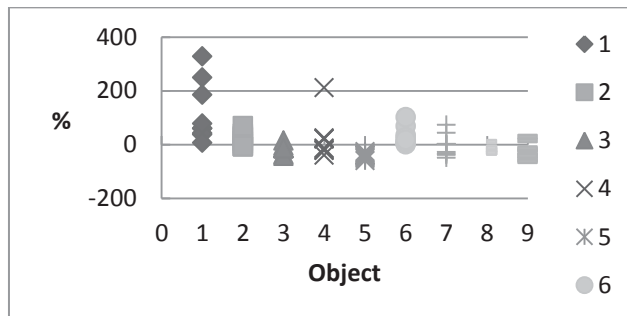


Figure 2 Error Rate Distribution of Class 1 Pilot Candidates (by object order)

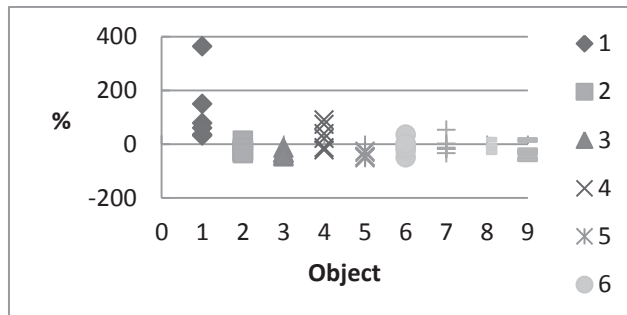


Figure 3 Error Rate Distribution of Class 3 Pilot Candidates (by object order)

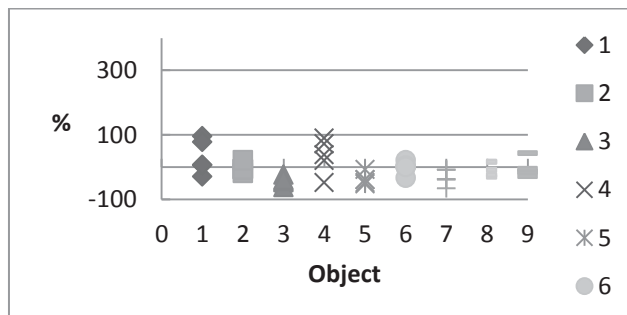


Figure 4 Error Rate Distribution of Master/Doctoral Students (by object order)

3.3.2 Error Rate Distribution by Distance

The Error Rate Distribution of all participants, Class 1 Pilot Candidates, Class 3 Pilot Candidates, and Master/Doctoral Students by distance are shown in Figure 5-8.

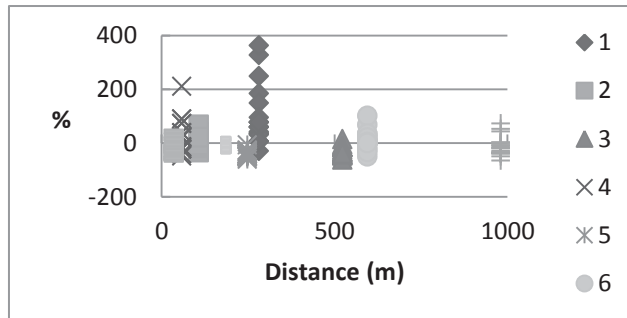


Figure 5 Error Rate Distribution of all participants (by distance)

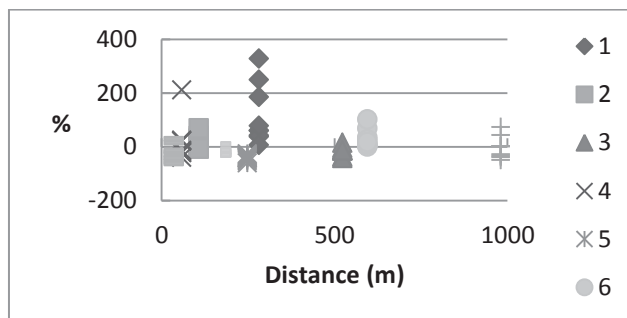


Figure 6 Error Rate Distribution of Class 1 Pilot Candidates (by distance)

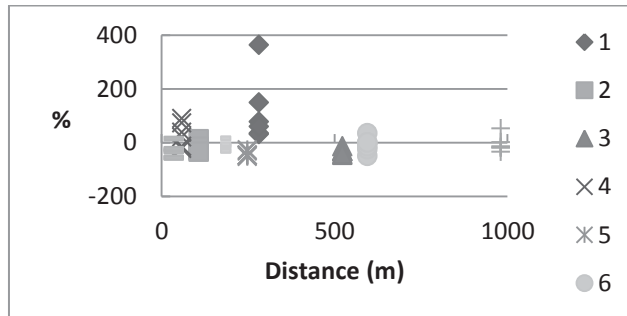


Figure 7 Error Rate Distribution of Class 3 Pilot Candidates (by distance)

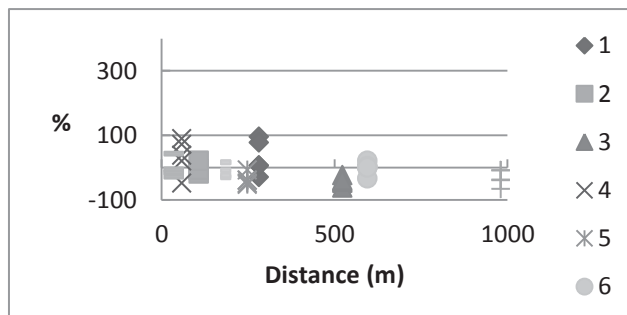


Figure 8 Error Rate Distribution of Master/Doctoral Students (by distance)

3.4 Discussion

According to the average of the estimating distance, Class 1 Pilot Candidates do better on object 4, 5, and 7; Class 3 Pilot Candidates do better on object 9; Master/Doctoral Students do better on the rest of objects. It seems that pilot candidates estimate more accurate on objects which are very close or very far.

However, standard deviations of the estimating distance show different results. Class 1 Pilot Candidates do better on object 5 and 8; Class 3 Pilot Candidates do better on object 3, 4, 5, and 9; Master/Doctoral Students do better on the rest of objects.

As it can be seen from the Error Rate Distribution figures, all the participants made huge mistakes on object 1 because of no reference. The error rate is up to over 350%. Participants tend to be overestimating when there is no reference. On the following objects, the error rates are almost between -50% and 100%. Another interesting phenomenon is that once participants find out themselves being overestimating, they will adjust their estimation to be underestimating. And the underestimating will continue until the next overestimating occurs. Surprisingly, Master/Doctoral Students with no experience onboard have better results on Error Rate Distribution. That means experience onboard has no necessary effect on visual sense. Despite the abnormal estimation on object 1 due to no reference, participants do better on distance between 100m and 600m. When the distance is too close or too far, error rates tend to be increased.

4. ANOMALY DETECTION

Before further analysis, the anomaly should be found out and eliminated. The Anomaly Detection procedure searches for unusual cases based on deviations from the norms of their cluster groups^[4]. It is used to find out which participant's estimation is different from the others of the group. This algorithm is divided into three stages^[5]:

(1) **Modeling.** Cases are placed into cluster groups based on their similarities on a set of input variables. The clustering model used to determine the cluster group of a case and the sufficient statistics used to calculate the norms of the cluster groups are stored.

(2) **Scoring.** The model is applied to each case to identify its cluster group and some indices are created for each case to measure the unusualness of the case with respect to its cluster group. All cases are sorted by the values of the anomaly indices. The top portion of the case list is identified as the set of anomalies.

(3) **Reasoning.** For each anomalous case, the variables are sorted by its corresponding variable deviation indices. The top variables, their values, and the corresponding norm values are presented as the reasons why a case is identified as an anomaly.

4.1 Modeling Stage

This stage performs the following tasks:

(1) **Training Set Formation.** Starting with the specified variables and cases, remove any case with extremely large values (greater than $1.0E+150$) on any continuous variable. Remove variables with all constant non missing values or all missing values. The remaining cases and variables are used to create the anomaly detection model.

(2) **Cluster Group Identification.** The processed input variables $\{X_k, k = 1, \dots, K + 1\}$ are used to create a clustering model. The two-step clustering algorithm is used with noise handling turned on.

(3) **Sufficient Statistics Storage.** The cluster model and the sufficient statistics for the variables by cluster are stored for the Scoring stage:

The grand mean M_k and standard deviation SD_k of each continuous variable are stored, $k \in \{1, \dots, K + 1\}$. For each cluster $h = 1, \dots, H$, store the size n_h . If X_k is a continuous variable, store the cluster mean M_{hk} and standard deviation SD_{hk} of the variable based on the cases in cluster h . If X_k is a categorical variable, store the frequency n_{hkj} of each category j of the variable based on the cases in cluster h . Also store the modal category M_{hk} . These sufficient statistics will be used in calculating the log-likelihood distance $d(h, s)$ between a cluster h and a given case s .

4.2 Scoring Stage

This stage performs the following tasks on scoring (testing or training) data:

(1) **New Valid Category Screening.** The scoring data should contain the input variables $\{X_{ok}, k = 1, \dots, K\}$ in the training data. Moreover, the format of the variables in the scoring data should be the same as those in the training data file during the Modeling

Stage. Cases in the scoring data are screened out if they contain a categorical variable with a valid category that does not appear in the training data.

(2) **Assign Each Case to its Closest Non-Noise Cluster.** The clustering model from the Modeling Stage is applied to the processed variables of the scoring data file to create a cluster ID for each case. Cases belonging to the noise cluster are reassigned to their closest non-noise cluster.

(3) **Calculate Variable Deviation Indices.** Given a cases, the closest cluster h is found. The variable deviation index VDI_k of variable X_k is defined as the contribution $d_k(h, s)$ of the variable to its log-likelihood distance $d(h, s)$. The corresponding norm value is M_{hk} , which is the cluster sample mean of X_k if X_k is continuous, or the cluster mode of X_k if X_k is categorical.

(4) **Calculate Group Deviation Index.** The group deviation index GDI of a case is the log-likelihood distance $d(h, s)$, which is the sum of all the variable deviation indices $\{VDI_k, k = 1, \dots, K + 1\}$.

(5) **Calculate Anomaly Index and Variable Contribution Measures.** Two additional indices are calculated that are easier to interpret than the group deviation index and the variable deviation index.

The anomaly index of a case is an alternative to the GDI, which is computed as the ratio of the case's GDI to the average GDI of the cluster to which the case belongs. Increasing values of this index correspond to greater deviations from the average and indicate better anomaly candidates.

A variable's variable contribution measure of a case is an alternative to the VDI, which is computed as the ratio of the variable's VDI to the case's GDI. This is the proportional contribution of the variable to the deviation of the case. The larger the value of this measure is, the greater the variable contributes to the deviation.

4.3 Reasoning Stage

Every case now has a group deviation index and anomaly index and a set of variable deviation indices and variable contribution measures. The purpose of this stage is to rank the likely anomalous cases and provide the reasons to suspect them of being anomalous.

(1) **Identify the Most Anomalous Cases.** Sort the cases in descending order on the values of the anomaly index. The top $pct_{anomaly}$ % (or alternatively, the top $n_{anomaly}$) gives the anomaly list, subject to the restriction that cases with an anomaly index less than or equal to $cutpoint_{anomaly}$ are not considered anomalous.

(2) **Provide Reasons for Considering a Case Anomalous.** For each anomalous case, sort the variables by their corresponding VDI_k values in descending order. The top $k_{anomaly}$ variable names, its value (of the corresponding original variable X_{ok}), and the norm values are displayed as reasoning.

4.4 Calculation

The results of Anomaly Detection are shown in Table 4. It is obvious that estimation of Class 1 Pilot Candidate 3 is different from others. So to ensure the accuracy of the following analysis, it should be eliminated.

Table 4 Anomaly Detection

Participant	Anomaly	Anomaly Index	CPeer Group	Field -1	Field Impact-1	Field -2	Field Impact-2	Field -3	Field Impact-3
Class 1 Pilot 1	F	0.994	1	107	0.179	523	0.148	35	0.141
Class 1 Pilot 2	F	0.732	1	35	0.192	58	0.124	981	0.119
Class 1 Pilot 3	T	1.794	1	58	0.271	595	0.119	35	0.117
Class 1 Pilot 4	F	0.927	1	981	0.199	35	0.178	107	0.12
Class 1 Pilot 5	F	0.706	1	58	0.138	523	0.132	35	0.129
Class 1 Pilot 6	F	1.142	1	981	0.3	281	0.255	523	0.081

Class 1 Pilot 7	F	0.839	1	58	0.149	172	0.132	248	0.129
Class 1 Pilot 8	F	1.597	1	595	0.257	107	0.235	523	0.202
Class 1 Pilot 9	F	0.753	1	248	0.173	281	0.133	523	0.123
Class 3 Pilot 1	F	1.184	1	281	0.302	595	0.192	107	0.1
Class 3 Pilot 2	F	0.855	1	35	0.163	58	0.143	523	0.141
Class 3 Pilot 3	F	0.91	1	172	0.247	107	0.152	595	0.133
Class 3 Pilot 4	F	0.855	1	35	0.163	248	0.152	107	0.138
Class 3 Pilot 5	F	0.929	1	981	0.249	172	0.119	58	0.105
Class 3 Pilot 6	F	0.848	1	107	0.19	35	0.166	523	0.118
M/D Student 1	F	1.171	1	248	0.371	981	0.161	523	0.103
M/D Student 2	F	1.091	1	523	0.22	172	0.206	58	0.13
M/D Student 3	F	0.901	1	172	0.25	595	0.168	523	0.111
M/D Student 4	F	0.719	1	172	0.154	281	0.14	981	0.136
M/D Student 5	F	1.054	1	35	0.282	58	0.116	248	0.103

5. TWO-STEP CLUSTERING ANALYSIS

To find out the difference between participants with and without experience onboard, cluster analysis is used. After the test calculation, the most efficient method, Two-Step Cluster Algorithms is chosen. As the name implies, the Two-Step clustering algorithm involves two steps: Pre-clustering and Clustering^{[6][7]}.

5.1 Pre-cluster Step

The pre-cluster step uses a sequential clustering approach. It scans the data records one by one and decides if the current record should be merged with the previously formed clusters or starts a new cluster based on the distance criterion.

The procedure is implemented by constructing a modified cluster feature (CF) tree. The CF tree consists of levels of nodes, and each node contains a number of entries. A leaf entry (an entry in the leaf node) represents a final sub-cluster. The non-leaf nodes and their entries are used to guide a new record quickly into a correct leaf node. Each entry is characterized by its CF that consists of the entry's number of records, mean and variance of each range field, and counts for each category of each symbolic field. For each successive record, starting from the root node, it is recursively guided by the closest entry in the node to find the closest child node, and descends along the CF tree. Upon reaching a leaf node, it finds the closest leaf entry in the leaf node. If the record is within a threshold distance of the closest leaf entry, it is absorbed into the leaf entry and the CF of that leaf entry is updated. Otherwise it starts its own leaf entry in the leaf node. If there is no space in the leaf node to create a new leaf entry, the leaf node is split into two. The entries in the original leaf node are divided into two groups using the farthest pair as seeds, and redistributing the remaining entries based on the closeness criterion.

If the CF tree grows beyond allowed maximum size, the CF tree is rebuilt based on the existing CF tree by increasing the threshold distance criterion. The rebuilt CF tree is smaller and hence has space for new input records. This process continues until a complete data pass is finished.

All records falling in the same entry can be collectively represented by the entry's CF. When a new record is added to an entry, the new CF can be computed from this new record and the old CF without knowing the individual records in the entry. These properties of CF make it possible to maintain only the entry CFs, rather than the sets of individual records. Hence the CF-tree is much smaller than the original data and can be stored in memory more efficiently.

Note that the structure of the constructed CF tree may depend on the input order of the cases or records. To minimize the order effect, randomly order the records before building the model.

5.2 Cluster Step

The cluster step takes sub-clusters (non-outlier sub-clusters if outlier handling is used) resulting from the pre-cluster step as input and then groups them into the desired number of clusters. Since the number of sub-clusters is much less than the number of original records, traditional clustering methods can be used effectively. Two-Step uses an agglomerative hierarchical clustering method, because it works well with the auto-cluster method.

Hierarchical clustering refers to a process by which clusters are recursively merged, until at the end of the process only one cluster remains containing all records. The process starts by defining a starting cluster for each of the sub-clusters produced in the pre-cluster step. All clusters are then compared, and the pair of clusters with the smallest distance between them is selected and merged into a single cluster.

After merging, the new set of clusters is compared, the closest pair is merged, and the process repeats until all clusters have been merged. Because the clusters are merged recursively in this way, it is easy to compare solutions with different numbers of clusters. To get a five-cluster solution, simply stop merging when there are five clusters left; to get a four-cluster solution, take the five-cluster solution and perform one more merge operation, and so on.

5.3 Calculation

The results of Cluster Analysis calculation are shown in Table 5. As it can be seen from the table, most of the Master/Doctoral Students, one Class 1 Pilot Candidate, and two Class 3 Pilot Candidates are in the same cluster. That means their choices are similar. The rest of the participants, who are mainly pilot candidates, are in the other cluster. It is indicated from the table, there are certain differences existing between participants with and without experience onboard.

Table 5 Cluster Analysis

Participant	Object									cluster
	1	2	3	4	5	6	7	8	9	
Class 1 Pilot 1	450	150	500	70	170	800	600	120	15	1
Class 1 Pilot 2	385	110	335	48	145	650	650	140	40	2
Class 1 Pilot 4	450	135	450	72	145	620	1400	120	13	1
Class 1 Pilot 5	400	120	450	45	150	750	1000	150	20	1
Class 1 Pilot 6	1200	100	450	70	160	600	1700	135	25	1
Class 1 Pilot 7	800	100	300	35	120	650	1000	120	20	1
Class 1 Pilot 8	500	180	600	45	130	1200	1000	120	28	1
Class 1 Pilot 9	300	100	450	50	180	700	700	150	30	1
Class 3 Pilot 1	1300	80	350	50	130	300	800	120	25	1
Class 3 Pilot 2	500	120	280	110	120	800	1000	150	15	1
Class 3 Pilot 3	700	75	360	70	130	450	850	200	23	2
Class 3 Pilot 4	380	80	450	100	180	600	800	150	15	1
Class 3 Pilot 5	370	90	360	45	170	510	1500	120	27	1
Class 3 Pilot 6	450	70	300	80	130	600	650	160	40	2
M/D Student 1	550	87	280	70	230	720	340	157	25	1
M/D Student 2	200	100	200	30	130	600	900	200	30	2
M/D Student 3	500	100	300	100	150	400	900	200	30	2
M/D Student 4	300	100	400	80	150	620	600	120	33	2
M/D Student 5	300	130	320	110	120	600	615	130	50	2

6. CONCLUSIONS

According to the results and analyses, the conclusions are as follows:

- Reference is important for estimating distance. Participants tend to be overestimating when there is no reference.
- When the distance is too close or too far, error rates tend to be increased.
- Once participants find out themselves being overestimating, they will adjust the estimation to be underestimating. And the underestimating will continue until the next overestimating occurs.
- Experience onboard has no necessary effect on visual sense. However, there are certain differences existing between participants with and without experience onboard.

It is obvious that, although visual observation is one of the most basic and important look-out methods, estimating the distance by sight according to OOWs' visual sense is not reliable, especially on the open sea where there is no object of reference. The ranging equipment, such as Radar, is necessary to assist OOW to make a full appraisal of the situation and of the risk of collision. It is also to be noted that, experienced OOWs, no matter how long they have been working onboard, should not be overconfidence on their distance estimating abilities. There is no necessary connection between the experience onboard and the accuracy of visual sense, although it seems that with or without the experience, certain differences do exist in distance estimating.

The conclusions above can be used for improving the look-out and enhancing the safety of the navigation. Further research need to be done with more participants, more specific studies on the brightness, contrast, background, and so on.

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