# SUBJECTIVE AND OBJECTIVE EVALUATION OF DATA QUALITY VISUALIZATION METHODS ON NAVIGATIONAL CHARTS

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## Introduction

Nautical charts are compiled with bathymetric data that differ in the year and method collected over areas varying from stable to mobile seafloor. Data quality on Electronic Navigational Charts (ENCs) is mainly encoded as an overlay of polygonal regions, each assigned a Category Zone of Confidence (CATZOC) based on the positional and attribute accuracy of depth measurements and the completeness of the collected data. With CATZOC seafarers may estimate where it is safe to navigate, including areas of minimal underwater clearance, and where improved awareness is required for the presence of uncharted, or poorly charted, hazards. Failing to account for the varying data quality may result in maritime accidents, environmental disasters, and loss of life (e.g., (BSU, 2020; DSB, 2017; RMIMA, 2020))

Nautical cartography is undergoing major changes with the development of new data standards and products based on the S-100 framework (IHO, 2018; Kastrisios et al., 2022). This includes the transition from CATZOC to the new composite data quality indicator for ENCs, the *Quality of Bathymetric Data* (QoBD). The CATZOC alphanumeric codes (A1, A2, B, C, D) are replaced by a numerical scheme (1 for best quality and 5 for worst) with one more category O ("Oceanic") for areas of depths greater than 200m ("U" for unassessed remains). Furthermore, the relevant committees of the International Hydrographic Organization (IHO) have decided on replacing the current star symbology that has been proven problematic (see Kastrisios et al., 2020).

One potential solution for the data quality sectors' visualization is with the use of see-through textures consisting of countable elements. In this work we discuss the proposed coding schemes (*Lines* and *Dot-Cluster*) and the results of an online user survey and an in-lab experiment for their evaluation compared to three alternatives (*Opaque-Colors*, *Color-Transparency*, and *Color-Textures*). Furthermore, we discuss how the results compare to previous works on uncertainty visualization and how the concept of *countable textures* could be extended for other uses.

## Methods

Reluctance to change has been identified as one of the main human related deficiencies by professionals in the hydrography/ nautical cartography domain (see Kastrisios &

Calder, 2021). Nevertheless, the results of a poll we conducted among professional hydrographers and nautical cartographers suggest that QoBD is well received by the community (Figure 1).

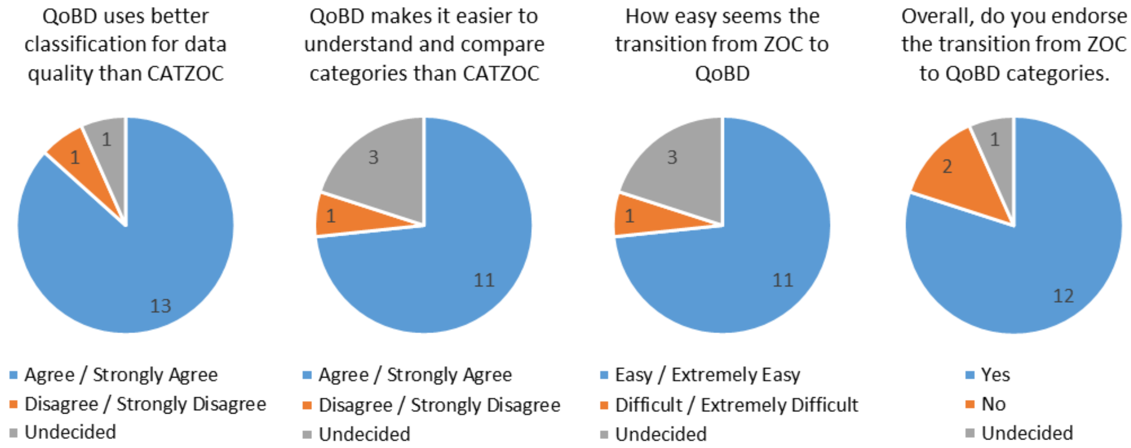


Figure 1. Poll results on the CATZOC-to-QoBD transition.

In tackling the research problem for the visualization of data quality sectors on ENCs, we developed a set of five requirements for the effective visualization of bathymetric uncertainty on charts: minimally interfere with the charted information; unambiguously relate to the QoBD categories; emphasize areas of greater uncertainty; be memorable; be effective in different ship navigation system light luminance modes (Kastrisios et al., 2020). Following an evaluation of the individual visual variables for meeting the requirements, the use of textures combining visual variables seemed most promising for the application. This led to the concept of *countable textures*, realized through two coding schemes: one consisting of lines (*Lines*) and one of clusters of dots (*Dot-Clusters*). Each level is qualitative distinct and visually denser to represent areas of greater uncertainty, while there is a direct correspondence of the element count to the visualized QoBD level, i.e., one line (or dot) for QoBD 1, two for QoBD 2, etc. The coding schemes' development followed an iterative process with several improvements. For instance, we initially used squares as the base symbol (Figure 2), however, circular symbols (dots) interfered less with depth labels while they resulted in smaller glyphs (see, e.g., Mańk, 2019; Rytz et al., 1980) for minimum perceivable sizes of circles and squares).

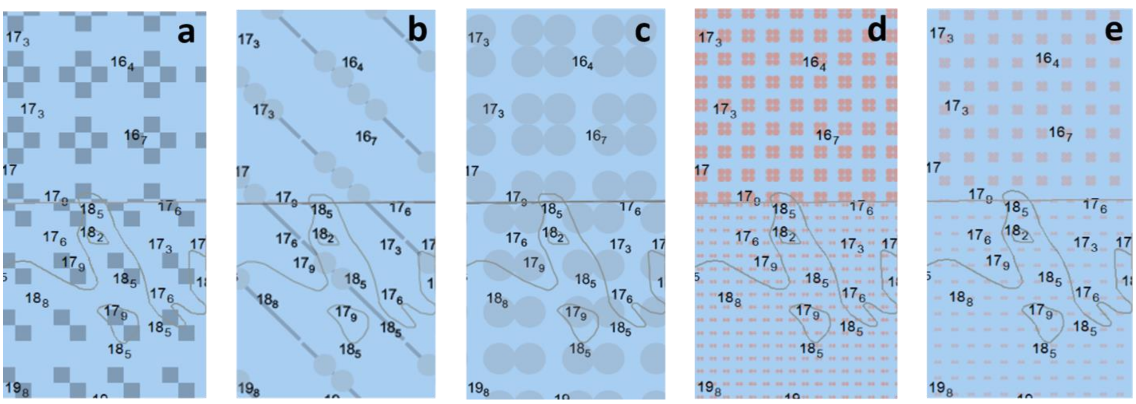


Figure 2. The evolution of dot-clusters from (a) textures consisting of squares and (b) circles-on-line to dots with improvements in (c, d, e) size, color, density, transparency.

For comparison we developed two more conventional methods of color schemes (*Opaque-Colors* and *Transparent-Color*), based on ideas discussed within IHO, and one combining textures and colors (*Color-Textures*) to overcome the obscuring and color blending of background information with color overlays (Figure 3).

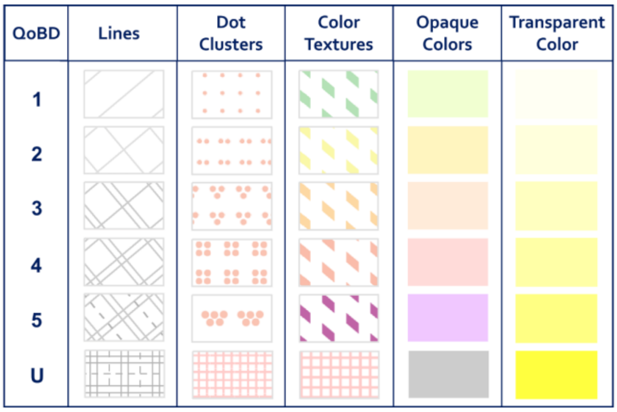


Figure 3. The alternative coding schemes for the visualization of the QoBD.

For evaluation we developed a survey for professionals in the field, consisted of 17 questions (16 subjective and one objective that tested respondent's ability to recognize the visualized QoBD) in four evaluation areas (Figure 4), and two final rankings where respondents ranked the schemes from best (1) to worst (5). The survey design and analysis are detailed in Kastrisios & Ware (2022).

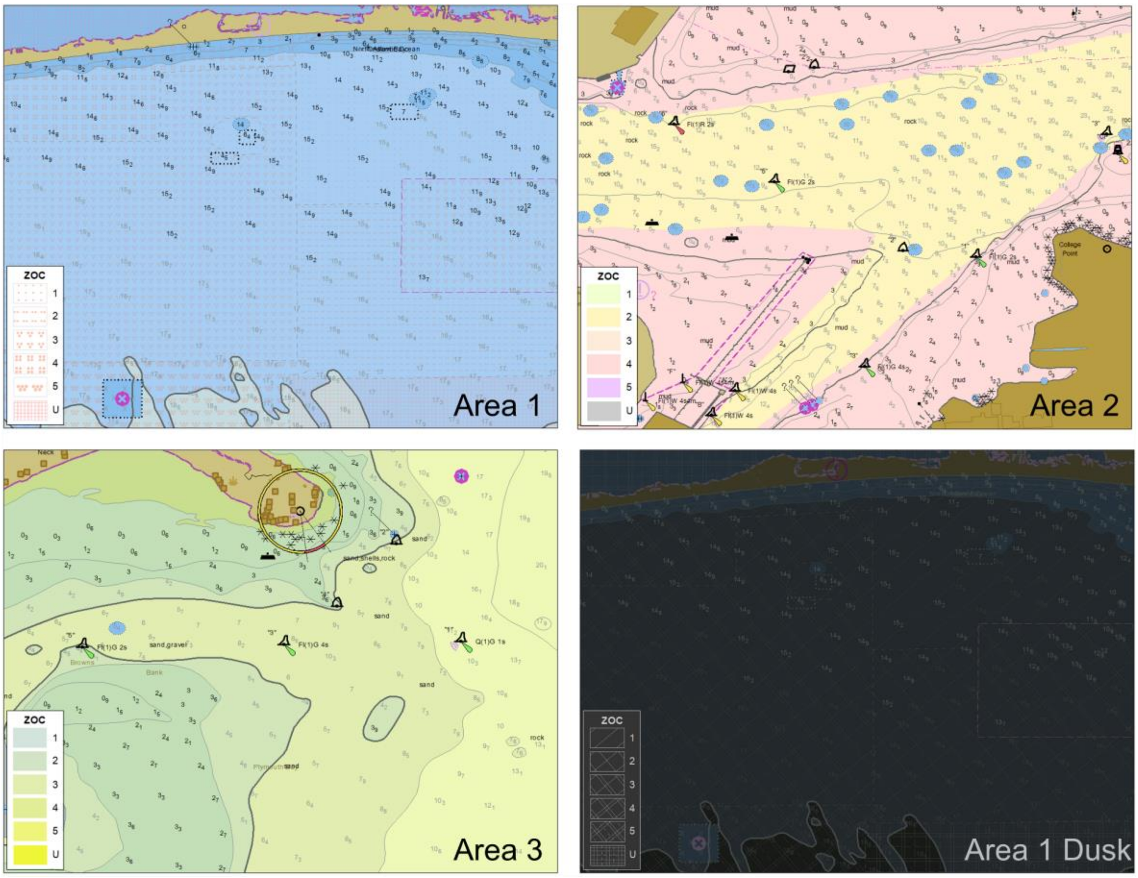


Figure 4. The four survey evaluation areas.

To further investigate the performance of the coding schemes, we run an in-lab experiment to objectively test the speed and accuracy of decoding the visualized QoBD levels with the alternative coding schemes (EXPT1) and their memorability in the absence of a key (EXPT2). We used an in-house developed chart generation software to create chart-like displays as the map background for QoBD coded overlays (Figure 5). This allowed for generating a new chart-like background for each trial, based on random parameters, with the aim to eliminate familiarity effects and easily tune stimuli to answer different questions; using screenshots from actual ENCs only a limited number of evaluation backgrounds would be possible. For details, the reader is referred to Ware & Kastrisios (2022).

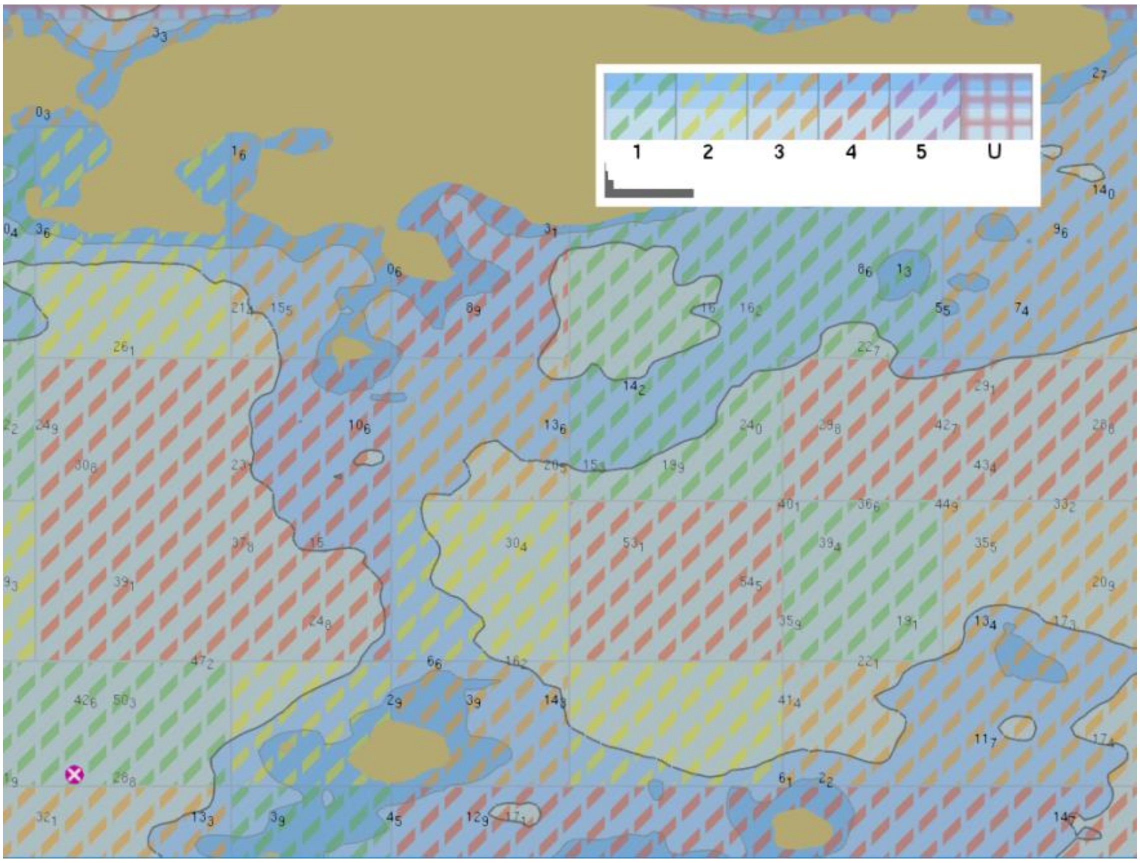


Figure 5. Example of synthetic chart display with *Color-Textures*.

**Results**

Survey participants ranked the countable textures the best (*Lines*) and second best (*Dot-Clusters*), followed by *Opaque-Colors* (Figure 6). Lines received the most positive ratings overall. Besides being participants' first choice in rankings, *Lines* was the only coding scheme with mean ratings over three in all four evaluation areas and against the five requirements. *Transparent-Color* and *Color-Textures* performed generally worse than the other three, and particularly the latter that failed in most survey questions. In Figures 6 and 7, statistically significant differences are denoted by the group letters A, B, and C: schemes that share a letter (e.g., A and AB) are not statistically different.

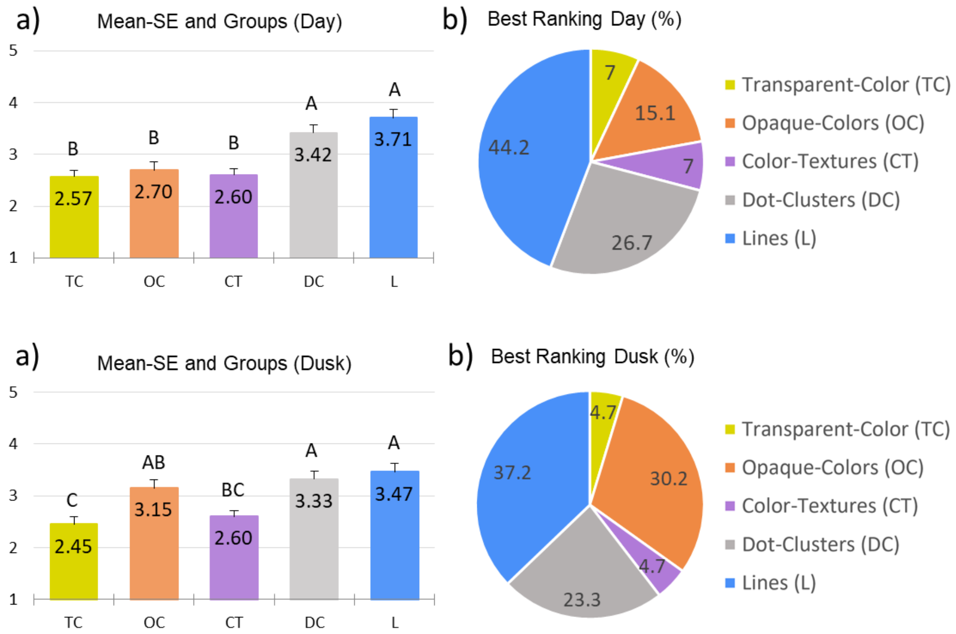


Figure 6. Rankings' means and groups (a) and best ranking percentages (b) in Day (top) and Dusk (bottom) system modes.

In the objective experiment, *Dot-Clusters* produced the fastest response times and the lowest error rates, followed by *Lines* and *Opaque-Colors* (Figure 6). On the other hand, the *Transparent-Color* yielded the slowest response times and very high error rates in the experiment.

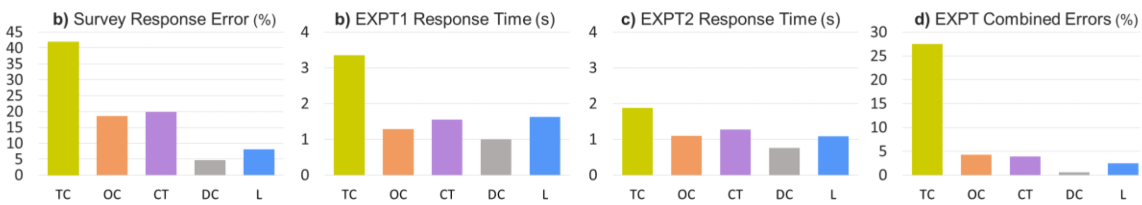


Figure 7. a) User survey objective question error rates and b), c), d) in-lab experiment results.

## Discussion and Conclusion

Textures with countable elements for the representation of data quality in the ordinal level is one of the novel contributions of this work. They were preferred over color overlays in survey rankings, while they resulted in lower error rates in the interpretation of the visualized data quality level. The latter was particularly prominent in the case of *Dot-Clusters* in the experiment. Overall, the results for the *Lines* and *Dot-Clusters* textures are consistent with previous works that recommend the use of textures for signifying uncertainty for areal objects with coincident visualizations (e.g., Kunz et al., 2011). This was not confirmed for the *Color-Textures* scheme by the survey results, which, however, performed better in the experiment.

Putting the results of this work into the greater context of visualizing data uncertainty, the use of color hues (*Opaque-Colors*) was rated highly in emphasizing worse quality data. This contradicts previous studies (e.g., MacEachren et al., 2012), however, the good performance in our work may be the result of selecting colder-to-warmer colors to denote certain-to-uncertain data.

Likewise, *Transparent-Color* scheme (which combines different levels of transparency and color saturation) was also found effective in emphasizing areas of worse quality data. Transparency is commonly cited as an effective visual metaphor of uncertainty, whereas literature is divided in regard to saturation (e.g., Kinkeldey et al., 2014; Kunz et al., 2011; MacEachren et al., 2005). Further work is required to derive a better understanding of the performance of these two visual variables over complex map backgrounds.

The considerably higher error rates of the color-based schemes in the objective survey question compared to the experiment demonstrated respondents' difficulty in assessing data quality when not all categories are present in the display. Countable textures showed a better behaviour in both situations. Map makers should consider this limitation of abstract symbols when not all levels may be displayed on maps (e.g., due to zoom in/out), while it raises the question of whether the countable textures method may be used for other applications. Generally, only a few levels are needed for representing uncertainty, while other map quantities often require greater granularity. To generalize the method, standard deviations might be computed over a surface and converted to steps, e.g., the series 0.5, 1.0, 1.5, 2.0, 2.5 would provide five steps. Extending countable textures to provide more steps could be with adding a symbol to represent the quantity 5, e.g., similarly to Wind Barbs in meteorology. However, a series of textures with many countable steps may no longer be readable "at a glance".

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