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REVIEW ARTICLE

Statistical Summary Perception in Vision

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Abstract | In the last 15 years, significant efforts have been made to investigate statistical processing of object information. This includes computing properties such as mean or variance of features of multiple objects present in a visual display. Unlike visual search performance for individual objects, which is typically dependent on set size, mean estimation is usually not dependent on set size. The paper reviews studies on the nature of representations used in statistical processing and consolidation of the relevant information in working memory. The paper also discusses the different attributes such as orientation, size and emotions that have been studied in the context of estimating the mean of those attributes. One prominent question is the role of attention in statistical processing. While some argue that attention is not needed for statistical processing, others argue that attention or in some cases distributed attention is necessary for statistical processing. The paper critically evaluates the opposing views and also presents possible issues that need to be resolved in future.

Keywords: *Statistical summary, Focused attention, Distributed attention, Mean, Capacity limitations, Diversity, Stable perception, Awareness, Perceptual grouping, CDA*

1 Introduction

The perception of the visual world around us consists of scenes that contain objects and perceiving the relationships between objects over space and time. In addition to perception of objects, humans also perceive global properties of scene such as gist perception. When there are multiple objects in a scene sharing a particular feature, then the human visual system appears to be able to perceive the mean value of that feature, if that feature varies along a continuous dimension. This is called statistical summary perception or ensemble perception. In addition to the mean, participants are able to perceive variability of features of objects in a display. Common features with which statistical summary perception have been studied include orientation, size, motion, and emotions[1,2].

This paper reviews work on statistical summary perception in vision primarily focusing on work performed in the last 15–20 years and older work on statistical summary perception has been covered elsewhere[3]. While the visual system is sensitive to higher order statistical properties, it is usually difficult to report those higher order statistical properties. This paper focuses mainly on the perception of the mean of a feature in displays containing multiple objects containing that feature.

2 Perception of the Mean

Perceiving or identifying an object in a display with multiple objects is usually capacity limited and performance decreases as the number of objects increase. Humans can focus their attention on only four objects at a time when they are asked to track moving objects[4,5]. Statistical summary perception, in general, is not influenced by the number of items in the display[2,6–12]. While participants had difficulty reporting the size of individual circles in the display, they were able to report the mean size of circles with set sizes greater than four[7]. Judgment of mean size is not

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much influenced by properties other than set size as well including the density of items[11] as well as the duration of the display[13]. It has also been shown that the features of the previously attended object influence mean judgments[14].

Participants not only perceive mean sizes but they adapt to the mean size of dots present in a display[15,16]. In their study, there was an initial display consisting of two sets of circles with different sizes with one set on the right side and another on the left side of fixation presented for 1 min. The two sets differed in terms of the mean size (diameter) of the circles. After the adapting display, two new sets of dots were presented on either side of the display and participants were asked which side had the larger mean size. The results showed that the test set that appeared on the same side as the larger mean size adapting set was perceived to have smaller mean size and vice versa for the test set that appeared on the same side as the smaller mean size adapting set.

Mean judgments have been shown for multiple features of objects present in a display including orientation[17], motion[18,19], gender[20], and emotions[1,2,12,20–22]. For example, multiple studies have shown that participants that who were shown a set of emotional faces in a display are able to judge the mean emotions of those emotional faces[1,2,12,20–22]. The mean emotion is perceived even with very short display durations of 50 ms [22].

How do we compute statistical summaries such as the mean? One possible method would be pooling the features of all objects in the display and compute the mean[1,6]. If individual feature distributions were independent, then the mean would have less variance and would have better precision. Once the mean is computed, individual features can be eliminated, provided there is no task requirement to remember them. Another possibility is that the individual features are poorly represented and hence would be difficult to judge, especially if the size is high. In computing the mean, different weightage algorithms (equal weight or weights based on precision) can be used with some of the items contributing more to the mean than others. The pooling of local distributions to obtain a global mean estimate can be useful for other vision tasks such as visual search[1]. The issue of whether information from all or most of the items is pooled together or only a small number of items are used to estimate the mean will be discussed in Sect. 4.2.

2.1 Perceptual Grouping and Statistical Summary

Gestalt psychologists have argued that the whole is different from the sum of its parts, and the statistical summary perception is an aspect of the whole. Averaging has been shown to be influenced by perceptual grouping[23]. Individual members who belong to a group defined by proximity were remembered much better than when they were not grouped together by proximity[23]. Given the possible close relationship between perceptual organization and statistical summary, the role of statistical summary and grouping in estimating size has been investigated recently[24]. The experiment used a display consisting of circles grouped by similarity, proximity, connectedness and common region. Participants had to remember the individual sizes of a subset of circles. Errors were correlated for circles from within a group compared to circles when they were not from the same group. In addition, the size of the circles was biased by the mean size of the group to which they belonged and the total error in individual size estimates were reduced due to the mean size bias. The results indicate that perceptual organization influences the computation of mean size, which further influences individual estimates.

3 Time Course of Statistical Summary Perception

Gist of scenes is perceived fairly quickly[25]. Studies have looked at the time course of statistical summary perception in comparison to identification of individual objects[9]. The time course of consolidation of information critical for statistical summary perception was studied using a masking paradigm. The display consisted of circular discs of different sizes. The number of circular discs was two or four in a display. The consolidation of representations associated with mean size of discs (mean task) in the display or identifying a particular sized disc (member task) was interrupted by presenting a mask at different time intervals following the stimulus display. After one second, a display with two choices was given for both mean and member tasks and the participant was asked to choose the appropriate target. In the member task, participants indicated the test disc that matched the size of any of the discs shown in the display. In the mean task, participants indicated the test disc that matched with the mean size of all the discs shown in the display.

In general, performance was better in the mean task compared to the member task.

Performance also increased with SOA between stimulus display and mask. While performance in the mean task did not depend on set size, performance in the member task was better with set size of 2 compared to set size of 4. Asymptotic performance was reached much earlier (133 ms SOA) in the mean task compared to the member task, indicating that the statistical information is computed and consolidated much earlier than individual discs even with small set size of 2 well within the capacity limits of visual short-term memory[9].

Statistical summaries are not just perceived when different objects are presented across space but also over time[21,26]. In a study with emotional expressions[21], twenty emotional faces were presented at a frequency of 20 Hz and participants were asked about the mean expression. Participants were able to do the task indicating mean can be computed over time.

The computation of statistical summary over time may not give equal weight to all the objects in a temporal stream[26]. The study evaluated different weights given to member objects in a stream for four different features: position, size, emotions and motion. The results showed that mean location was influenced more by objects that occurred early compared to those that occurred later in the stream. For the rest of the features (size, emotions and motion), the perception of the mean was influenced by objects that occurred later compared to earlier in the stream. The results also indicate that the process of mean computation could differ for different features, especially in terms of "what" and "where" information about objects.

4 Role of Attention

There has been an extensive debate on the role of attention in statistical summary perception ranging from (a) attention is not needed for statistical processing, (b) limited capacity focused attention is sufficient for statistical processing, and (c) distributed attention across a large number of items underlies statistical processing.

4.1 Is Attention Needed for Statistical Processing?

Given the rapid computation of statistical properties, it has been suggested that statistical computation involves a parallel but mostly automatic process combining information from featural representations of all the items in the display[6,12]. According to models of visual search such as the guided search model[27], gist of a scene is processed in a different pathway, which is not influenced by selective attention. However, both gist of a scene and individual object identification has to pass through a later bottleneck, which is also used to explain phenomena such as attentional blink[28].

Consistent with these views, some have argued that statistical processing can occur outside the focus of attention[29,30]. They used a multiple object tracking task in which participants tracked a set of dots among other dots. Participants were asked to report the mean location of the dots they tracked as well as dots they did not track. Performance with mean location identification was as good with the non-tracked dots as with the tracked dots[29]. In addition, participants who performed a tracking task were asked about differences in mean orientation of stimuli at the top and bottom halves of the display[30]. Participants were able to detect the differences in mean even though they simultaneously performed an attention-demanding task.

Evidence for the need for attention has been shown when participants are asked to perform both a member task in which observers had to identify a particular sized circle and a mean task in which observers had to identity the mean size of circles in the display[9] and were tested only in one of the tasks in a given trial. Performance in mean size task was also reduced indicating that attention is needed to perform the mean task as well. Evidence for summary statistics is also possibly influenced by attention comes from other studies as well[31,32]. Other studies, which will be discussed in the next section, have argued that not only attention is needed but more specifically distributed attention is important for statistical summary perception[8].

The issue of the necessity of attention for computing statistical summaries has also been studied through the measure of diversity[33–36]. It has been argued that attention is not necessary for perceiving hue diversity[33]. In their study, they showed four rows of coloured letters preceded by a cue that indicated the row from which participants had to report a letter. This was followed by a question on colour diversity of either cued or uncued rows. They manipulated independently the diversity of the cued and uncued rows resulting in four diversity conditions. Participants were able to report colour diversity for unattended letters. In addition, their performance with post-cued letters was not influenced by the colour diversity judgments. Using a variation of the paradigm used by Bronfman and colleagues[33], a follow-up study[34] investigated hue diversity perception in the context of attention. They again showed that hue diversity could be perceived under cases of very little attention. More importantly, they showed that hue diversity is perceived but changes to individual hues were not perceived even when all the hues of letters in a particular uncued row were changed. They argued hue diversity is perceived even though hue of individual objects was not consciously perceived and hue diversity computations occur unconsciously and without attention.

Argument against the position that hue diversity could be computed without attention comes from a study using the inattentional blindness paradigm[36]. Participants were asked to perform a primary task on a cued row keeping the hue diversity of uncued rows high. In the critical inattentional blindness trial, the hue diversity changed from high to low and participants were asked about the hue diversity. More observers failed to detect the change in hue diversity better than chance indicating the importance of attention for hue diversity.

It should be noted though that in the hue diversity experiments[33,34], a particular row is designated as attended or not attended based on cuing and lack of attention is inferred based on dual task performance (primary task performance independent of secondary task). While such an argument has been used in dual task situations, it is very difficult to show that something is not attended when there is an explicit task requirement. The results are consistent with attention being initially distributed throughout the display and then zooming in on to the cued row. Other studies have argued that initial distributed attention could be a default mode of operation[37]. The display duration in the hue diversity experiments[33,34] was 300 ms. It has been argued that information about statistical summaries are consolidated earlier and asymptotic performance can be reached at 133 ms[9]. Hence, there would have been ample time for an initial distributed attention to the display followed by zooming into the cued row.

4.2 Scope of Attention and Statistical Processing

An important aspect of attention is the scope of attention[10,38–40]. Scope of attention can be understood using the metaphor of a zoom lens whose setting (size of spotlight) can be changed depending on stimuli or task requirements. Scope of attention has been linked to changes in visual awareness[41] as well as emotional processing[42,43].

Many studies have argued that statistical computations are performed by pooling information from all or most items in the display[6,12]. An alternate proposal for statistical judgments is sub-sampling, i.e., the computation of mean size is based on sampling a small number of items in the display and not based on representations obtained from all the items in the display[44]. Simulations performed with sampling one to three circles showed that performance similar to humans could be achieved with one or two items. Focused attention on one or two items may be sufficient to explain statistical judgment performance.

Evidence against sub-sampling comes from multiple studies[8,45,46]. For example, Chong et al.[45] (Experiment 2) presented participants whole displays containing all the items or displays containing one or two items sampled from the same displays in the left or right side. Participants were asked to decide which side contained the larger mean size. Mean size judgments were better in the whole display compared to the sampled display. Showing all items in the display led to better mean size judgments indicating that all items in the display contributed to mean size and information from all or most of the items are pooled together possibly using distributed attention[45]. They also checked whether the estimated mean was influenced by items from locations close to fixation or randomly chosen from a set of locations. If focused attention is used for sub-sampling, then the chances of items near fixation being selected would be higher and would influence the estimated mean. They did not find any evidence for such a strategy.

The sub-sampling model[44] argues that sampling strategy may depend on stimulus size range. Better performance was shown for a narrow range of sizes with random sampling and a wider range of sizes with picking the two extremes (minimum and maximum size). This selection of strategy based on size range and its implications have been studied using displays manipulating size distributions: (a) homogenous display in which all sizes were the same (b) sizes picked from a uniform distribution, (c) bi-modal distributions and (d) heterogeneous[45]. If distributions of size change lead to selection of different strategies, then changing strategies would result in switching costs in mixed blocks that contain these distributions than blocks in which only one distribution was used. The experiment did not find a switching cost indicating that probably the same strategy was being used in the mixed distribution block as well the single distribution blocks, arguing in favour of the strategy proposed by the sub-sampling model.

Judgment of mean size was shown to be influenced by conditions that are linked to distributing attention and processing information in parallel across all the items in the display[46]. Mean judgment was better under conditions of pop-out search in which attention is more distributed compared to conjunction search in which attention is more focused[46]. The advantage for mean size judgment persisted even when objects were presented successively over time.

Additional evidence against sub-sampling comes from studies on mean emotion looking at the effect of outlier[12]. A random sub-sampling strategy would predict an effect of outliers moving the mean emotion estimate towards the outliers. The results showed that observers seem to exclude the outliers in estimating mean size indicating that information from multiple items is considered in computing the mean.

The sub-sampling hypothesis for statistical processing has also been tested by computing a neural measure obtained from ERPs[8]. An important measure that has been used to understand the capacity[47,48] and precision of representations[49] in working memory is contralateral delay activity (CDA). CDA is a difference waveform obtained by taking the difference between the contralateral and ipsilateral sides of the brain during the delay between the stimulus and recognition displays. CDA is typically seen in posterior electrodes.

In the CDA study[8], the display consisted of fifteen red- or green-coloured discs on the left and right side of the display. Participants were asked either to perform a mean task (remember the mean size of a set of circles) or member task (remember a particular sized circle) based on the red circles on the side of the display indicated by a cue. The set size of the red circles was manipulated (2, 4 and 8). Participants were given a 2 AFC task to indicate the target circle (depending on the task) 1500 ms after the presentation of the stimulus display.

ERPs were obtained during the stimulus display as well as the interval between stimulus display and response display. CDA amplitudes were computed for the 500–900 ms time window after stimulus onset. The behavioural results showed that the performance in the mean task was higher and constant across all set sizes. The performance in the member task was higher for small set sizes and decreased for set sizes of 4 and 8.

The results showed that with the member task, CDA amplitude increased with set size similar to the results obtained in earlier studies[47]. However, the CDA amplitude was high and did not change as a function of set size for the mean task. If CDA amplitude is interpreted to reflect working memory capacity[47], then the high amplitude even for small set sizes with the mean task implies that the working memory is fully loaded. It is to be noted that even with the small set size of 2, the CDA amplitude was significantly higher for the mean task compared to the member task indicating that sub-sampling or focusing attention on one or two objects for computing mean size is not the appropriate explanation. The results indicate that attention was perhaps distributed across a large number of subjects and the nature of representations used in statistical computations may differ and load working memory differently compared to those used for object recognition.

Evidence for the role of scope of attention also comes from other studies comparing single object perception with statistical summary perception[50]. Interference between featural information at individual object level or ensemble level was studied by manipulating texture and shape[50]. When the stimuli were manipulated so that global processing is required, there was interference between statistical summary features but there was no interference when local processing was required indicating the importance of broad scope of attention for statistical summary perception.

5 Development and Learning of Statistical Summary

5.1 Development and Summary Perception

There is very little work on the development of statistical summary perception over age[51]. Children (4–5 years of age) and adults were asked to perform a task based on size of oranges[51], that is pick a tree out of two that had larger size orange(s). Children were able to estimate mean size and respond better when information from all the oranges were available compared to when they were able to see only one orange. Overall adults did better than children but their advantage with ensembles compared to a subset was similar to that seen with children. More studies are needed to understand the development of statistical summary perception and see whether the development is similar for different features such as size and emotions. In addition, there is very little information how statistical summary perception changes over life span.

5.2 Learning and Summary Perception

There is very little work on the way we acquire the ability to perceive statistical summaries. One study has investigated the effect of learning and specific forms of feedback on learning statistical summary[52]. They asked participants to perform a pointing task to the centroid location.

Participants who received feedback about both distance and direction showed better performance in a different statistical summary task after training compared to before training.

Another aspect related to statistics is that we learn statistical regularities present in our environment. An intriguing result linking statistical summary perception and statistical learning is they may mutually interfere with each other[53]. It is not clear whether such mutual interference is modality specific or not and would vary based on different forms of statistical learning and statistical summary perception.

6 Awareness and Statistical Summary

One important issue with respect to awareness is the bandwidth of our conscious experience[35,54]. Some have argued that our conscious experience is sparse and limited by our attentional capacity[55]. Evidence for sparsity comes from phenomena such as change blindness[56,57] and inattentional blindness[58]. Others have argued that our conscious experience can overflow access[54]. Our visual experience is or at least seems to be rich in content. One argument to reconcile the richness of visual experience with our limitations to attend to more than four objects has been based on statistical summary perception[35]. While attended objects are processed at a high resolution, the entire scene is probably processed at a low resolution based on statistical summary and gist perception. This is also supported by evidence indicating that neural structures that underlie statistical summary and gist perception can be dissociated from those that underlie object perception[59]. It should be noted though statistical summary perception also is subject to attentional constraints[9,32], it is probably facilitated by default mode distributed attention usually with the onset of a visual display[37]. It has been argued that there is no need to assume overflow and postulate a separate and rich phenomenal awareness to explain the perception of statistical summaries or gist of a scene[35]. One response to the arguments for sparse visual experience has been to argue that observers are actually phenomenally conscious of ensembles and statistical summaries[60]. Experiments on hue diversity[34] have been used to argue that observers are aware of hue diversity without being aware of hues of individual objects and hence our conscious experience is still sparse. Further research on ensembles, gist and statistical summaries would help us further understand the nature of our visual experience.

7 Conclusions

The expanding research on statistical summary perception indicates that we are able to compute and perceive statistical parameters such as mean and variability across a range of visual features. While the studies reviewed indicate that a wealth of information is available, the mechanisms underlying statistical summary perception and their neural underpinnings for different aspects of visual objects are not well understood. There is reasonable evidence that information is pooled across features from multiple objects in obtaining statistical summaries and this can be achieved with less attention or more likely diffused attention. The computing of statistical summary using diffused attention may enable the identification of deviants in the visual field in comparison to the mean and explain some aspects of visual search[1,61] and rapid categorization[62]. The dependence of statistical summaries over time may enable us to maintain stable representations and help in perception[15,63]. The results on statistical summary perception also have implications for other important aspects of our mind including our phenomenal experience.

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