Shannon Entropy: A Possible Intrinsic Target Property*

by

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Abstract

We propose that the average total change of Shannon's entropy is a candidate for an *intrinsic* target property. An intrinsic target property is one that is completely independent of psychological factors and can be associated solely with a physical property of the target. We analyzed the results of two lengthy experiments that were conducted from 1992 through 1993 and found a significant correlation (Spearman's $\varrho = 0.337$, $df = 31$, $t = 1.99$, $p \leq 0.028$) with an absolute measure of the quality of the anomalous cognition (AC). In addition, we found that the quality of the AC was significantly better for dynamic targets than for static targets ($t=1.71$, $df=36$, $p \leq 0.048$). The 1993 correlation with the change of entropy replicated a similar finding from our 1992 study. Using monte carlo techniques, we demonstrate that the observed correlations were not due to some unforeseen artifact with the entropy calculation, but perhaps the correlation can be accounted for because of the difference in some other measure between static and dynamic targets. The monte carlo results and the significant correlations with static targets in the 1992 study, however, suggest otherwise. We describe the methodology, the calculations, and correlations in detail and provide guidelines for those who may wish to conduct similar studies.

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Introduction

The psychophysical properties of the five known senses are well known (Reichert, 1992). At the "front end," they share similar properties. For example, each system possesses receptor cells that convert some form of energy (e.g., photons for the visual system, sound waves for the audio system) into electrochemical signals. The transfer functions are sigmoidal; that is, there is a threshold for physical excitation, a linear region, and a saturation level above which more input produces the same output. How these psychophysical reactions translate to sensational experience is not well understood, but all the systems do possess an awareness threshold similar to the subliminal threshold for the visual system.

Since all the known senses appear to share these common properties, it is reasonable to expect that if anomalous cognition (*AC*)* is mediated through some additional "sensory" system, then it, too, should share similar properties at the pre-perceptual cellular front end. For example, a putative *AC* sensory system should possess receptor cells that have a sigmoidal transfer function and exhibit threshold and saturation phenomena. As far as we know, there are no candidate neurons in the peripheral systems whose functions are currently not understood. So, if receptor cells exist, it is likely that they will be found in the central nervous system. Since 1989, our laboratory has been conducting a search for such receptor sites (May, Luke, Trask, and Frivold, 1990); that activity continues.

There is a second way in which receptor-like behavior might be seen in lieu of a neurophysiology study. If either an energy carrier for *AC* or something that correlated with it were known, then it might be possible to infer sigmoidal functioning at the behavioral level as opposed to the cellular level. Suppose we could identify an intrinsic target property that correlated with *AC* behavior. Then, by manipulating this variable, we might expect to see a threshold at low magnitudes and saturation at high magnitudes.

To construct such an experiment, it is mandatory that we eliminate, as much as possible, all extraneous sources of variance and adopt an absolute measure for the *AC* behavior (Lantz, Luke, and May, 1994). We can reduce one source of variance by considering what constitutes a good target in an *AC* experiment. Delanoy (1988) reported on a survey of the literature for successful *AC* experiments and categorized the target material according to perceptual, psychological and physical characteristics. Except for trends related to dynamic, multi-sensory targets, she was unable to observe systematic correlations of *AC* quality with her target categories.

Watt (1988) examined the target question from a theoretical perspective. She concluded that the "best" *AC* targets are those that are meaningful, have emotional impact, and contain human interest. Those targets that have physical features that stand out from their backgrounds or contain movement, novelty, and incongruity are also good targets.

In trying to understand these findings and develop a methodology for target selection for process–oriented research, we have constructed a metaphor. Figure 1 shows three conceptual domains that contribute to the variability in *AC* experiments. The engineering metaphor of source, transmission, and detector allows us to assign known contributors to the variance in specific domains. Without controlling

* The Cognitive Sciences Laboratory has adopted the term *anomalous mentalphenomena* instead of the more widely known *psi*. Likewise, we use the terms *anomalous cognition* and *anomalous perturbation* for *ESP* and *PK*, respectively. We have done so because we believe that these terms are more naturally descriptive of the observables and are neutral in that they do not imply mechanisms. These new terms will be used throughout this paper.

or understanding these sources, interpreting the results from process-oriented research is problematical, if not impossible.

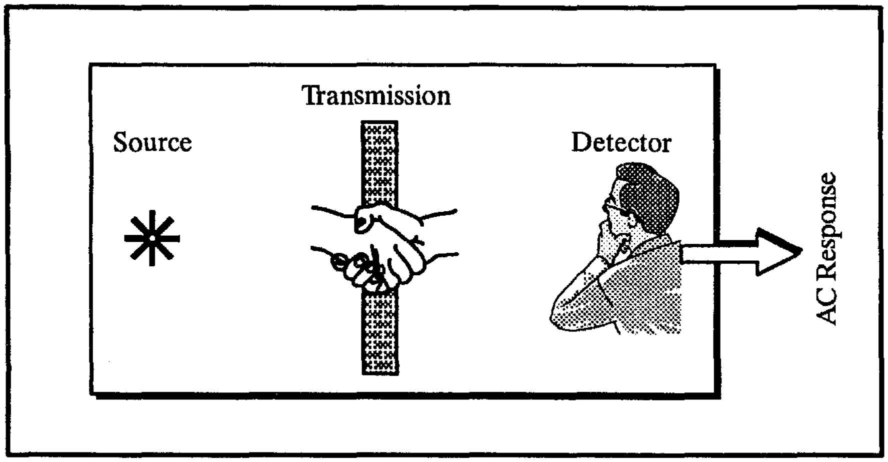

Figure 1. Information-transfer Metaphor

For example, suppose that the quality of an *AC* response actually depended upon the physical size of a target, and that affectivity was also a contributing factor. That is, a large target that was emotionally appealing was reported more often more correctly. Obviously, both factors are important in optimizing the outcome; however, suppose we were studying the effect of target size alone. Then an "attractive" small target might register as well as a less attractive large target and the size dependency would be confounded in unknown ways.

Our metaphor allows us to assign variables, such as these, to specific elements. Clearly, an individual's psychological response to a target is not an *intrinsic* property of a target; rather, it is a property of the receiver.* Likewise, size is a physical property of the target and is unrelated to the receiver. Generally, this metaphor allows us to lump together the psychology, personality, and physiology of the receiver and consider these important factors as contributors to a detector "efficiency." If it is true that an emotionally appealing target is easier to sense by some individuals, we can think of them as more efficient at those tasks. In the same way, all physical properties of a target are *intrinsic* to the target and do not depend on the detector efficiency. Perhaps, temporal and spatial distance between target and receiver are intrinsic to neither the target nor the receiver, but rather to the transmission mechanism, whatever that may be.

More than just nomenclature, our metaphor can guide us in designing experiments to decrease certain variabilities in order to conduct meaningful process-oriented research. Some of the methodological improvements seem obvious. If the research objective is to understand the properties of *AC* rather than understanding how an *AC* ability may be distributed in the population, then combining results across receivers should be done with great caution. To understand how to increase high jumping ability, for example, it makes no sense to use a random sample from the general population as high jumpers; rather, find a good high jumper and conduct vertical studies (no pun intended). So, too, is it true in the study of

* A person's psychological reaction to a target (i.e., "detector" efficiency) is an important contributing factor to the total response as indicated in the references sited above; however, it is possible to reduce this contribution by careful selection of the target pool material.

AC. We can easily reduce the variance by asking given receivers to participate in a large number of trials and not combining their results.

May, Spottiswoode, and James (1994) suggest that by limiting the number of cognitively differentiable elements within a target, the variance can also be decreased. A further reduction of potential variance can be realized if the target pool is such that a receiver's emotional/psychological response is likely to be more uniform across targets (i.e., reducing the detector variance as shown in Figure 1).

Having selected experienced receivers and attended to these methodological considerations, we could then focus our attention on examining *intrinsic* target properties. If we are successful at identifying one such property, then all process-oriented *AC* research would be significantly improved, because we would be able to control a source of variance that is target specific. The remainder of this paper describes the analysis of two lengthy studies that provide the experimental evidence to suggest that the average of the total change of Shannon's entropy may be one such intrinsic target property.

Approach

The *AC* methodological details for the two experiments can be found in Lantz, Luke, and May (1994). In this section, we focus on the target calculations and the analysis techniques.

Shannon Entropy: A Short Description

Building upon the pioneering work of Leo Szilard (1925, 1929), Shannon and Weaver (1949) developed what is now called information theory. This theory formalizes the intuitive idea of information that there is more "information" in rare events, such as winning the lottery, than in common ones, such as taking a breath. Shannon defined the entropy for a given system as the weighted average of the probability of occurrence of all possible events in the system. Entropy, used in this sense, is defined as a measure of our uncertainty, or lack of information, about a system. Suppose, for example, we had an octagonal fair die (i.e., each of the eight sides is equally likely to come up). Applying Equation 1, below, to this system gives an entropy of three bits, which is in fact the maximum possible for this system. If, on the other hand, the die were completely biased so that the same side always came up, the entropy would be zero. In other words, if each outcome is equally likely then each event has the maximum surprise. Conversely, there is no surprise if the same side always lands facing up.

In the case of images, a similar analysis can be used to calculate the entropy. For simplicity, consider a black and white image in which the brightness, or luminance, of each picture element, or pixel, is measured on a scale from zero to 255, that is, with an eight bit binary number. Equation 1 can again be used to arrive at a measure of the picture's entropy. As with the other sensory systems were gradients are more easily detected, we shall show that the gradient of Shannon's entropy is correlated with AC performance far better than the entropy itself.

In other sensory systems, receptor cells are sensitive to incident energy regardless of "meaning", which is ascribed as a later cognitive function. Shannon entropy is also devoid of meaning. The pixel analysis ignores anything to do with cognitive features. From this point of view, a photograph of a nuclear blast is, perhaps, no more Shannon-entropic than a photograph of a kitten; it all depends on the intensities, which were used to create the photographs. Thus, it is not possible to give a prescription on how to chose a high change-in-entropy photograph based on it pictorial content. Perhaps, after much experience, it may be possible to recognize good targets from their *intensity* patterns; at the moment we do not know how to accomplish this.

Target Calculations

Because of the analogy with other sensorial systems, we expected that the change of entropy would be more sensitive than would be the entropy alone. The target variable that we considered, therefore, was the average total change of entropy. In the case of image data, the entropy is defined as:

$$S_k = -\sum_{m=0}^{N_k} p_{mk} log_2(p_{mk}), \tag{1}$$

where p_{mk} is the probability of finding image intensity m of color k. In a standard, digitized, true color image, each pixel (i.e., picture element) contains eight binary bits of red, green, and blue intensity, respectively. That is, N_k is 255 (i.e., 2^8-1) for each k, $k = r, g, b$. For color, k, the total change of the entropy in differential form is given by:

$$dS_k = \left|\nabla S_k \cdot \vec{dr}\right| + \left|\frac{\partial S_k}{\partial t}\right| dt. \tag{2}$$

The first term corresponds to the change of the entropy spatially across a single photograph of video frame. Imagine a hilly plane in entropy space; this term represents the steepness of the slope of the hills (i.e., the change between adjacent macro-pixels, as defined below). The second term adds time changes to the total change. Not only does the entropy change across a scene, but a given patch of the photograph changes from one scene to the next. Of course this term is zero for all static photographs.

We must specify the spatial and temporal resolution before we can compute the total change of entropy for a real image. Henceforth, we drop the color index, k, and assume that all quantities are computed for each color and then summed.

To compute the entropy from Equation 1, we must specify empirically the intensity probabilities, p_m. In Lantz, Luke, and May's 1993 experiment, the targets were all video clips that met the following criteria:

- Topic homogeneity. The photographs contained outdoor scenes of settlements (e.g., villages, towns, cities, etc.), water (e.g., coasts, rivers and streams, waterfalls, etc.), and topography (e.g., mountains, hills, desserts, etc.).
- Size homogeneity. Target elements are all roughly the same size. That is, there are no size surprises such as an ant in one photograph and the moon in another.
- Affectivity homogeneity. As much as possible, the targets included materials which invoke neutral affectivity.

For static targets, a single characteristic frame from a video segment was digitized (i.e., 640×480 pixels) for eight bits of information of red, green, and blue intensity. The video image conformed to the NTSC standard aspect ratio of 4×3, so we arbitrarily assumed an area (i.e., macro-pixel) of $16 \times 12 = 192$ pixels from which we calculated the p_m. Since during the feedback phase of a trial the images were displayed on a Sun Microsystems standard 19-inch color monitor, and since they occupied an area approximately 20×15 cm square, the physical size of the macro-pixels was approximately 0.5 cm square. Since major cognitive elements were usually not smaller than this, this choice was reasonable—192 pixels were sufficient to provide a smooth estimate of the p_m.

For this macro-pixel size, the target frame was divided into a 40×40 array. The entropy for the (i,j)th macro-pixel was computed as:

$$S_{ij} = -\sum_{m=0}^{N-1} p_m \, log_2(p_m),$$

where p_m is computed empirically only from the pixels in the (i, j) macro-pixel and m is the pixel intensity. For example, consider the white square in the upper left portion of the target photograph shown in Figure 2.

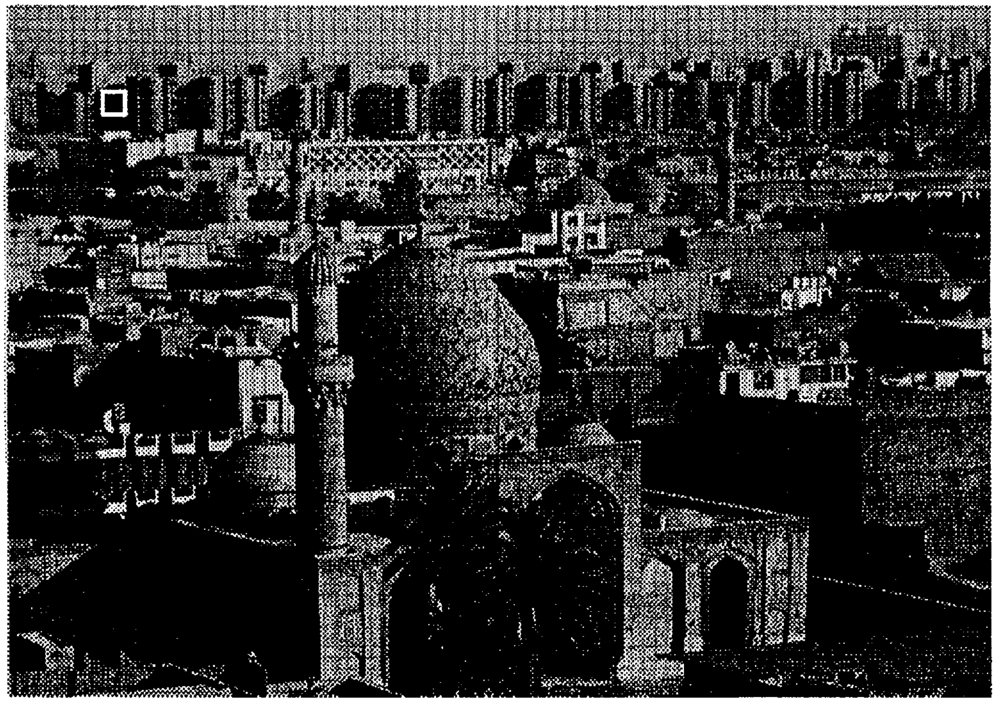

Figure 2. City with a Mosque

The green probability distribution for this macro-pixel (3,3) is shown in Figure 3. The probability density and the photograph itself indicate that most of the intensity in this macro-pixel is near zero (i.e., no intensity of green in this case). In a similar fashion, the S_{ij} are calculated for the entire scene. Since i and j range from zero to *40*, each frame contains a total of *1,600* macro-pixels.

We used a standard image processing algorithm to compute the 2-dimensional spatial gradient for each of the *1,600* macro-pixels. The first term in Equation 2 was approximated by its average value over the image and was computed by the relations shown as Equations 3.

$$\begin{aligned} |\nabla S_{ij} \cdot \vec{dr}| &= \sqrt{\left(\frac{dS_{ij}}{dx}\right)^2 + \left(\frac{dS_{ij}}{dy}\right)^2} \\ \frac{dS_{ij}}{dx} &\approx (S_{i+1,j+1} - S_{i+1,j-1}) + 2(S_{i,j+1} - S_{i,j-1}) + (S_{i-1,j+1} - S_{i-1,j-1}) \\ \frac{dS_{ij}}{dy} &\approx (S_{i+1,j+1} - S_{i-1,j+1}) + 2(S_{i+1,j} - S_{i-1,j}) + (S_{i+1,j-1} - S_{i-1,j-1}) \end{aligned} \tag{3}$$

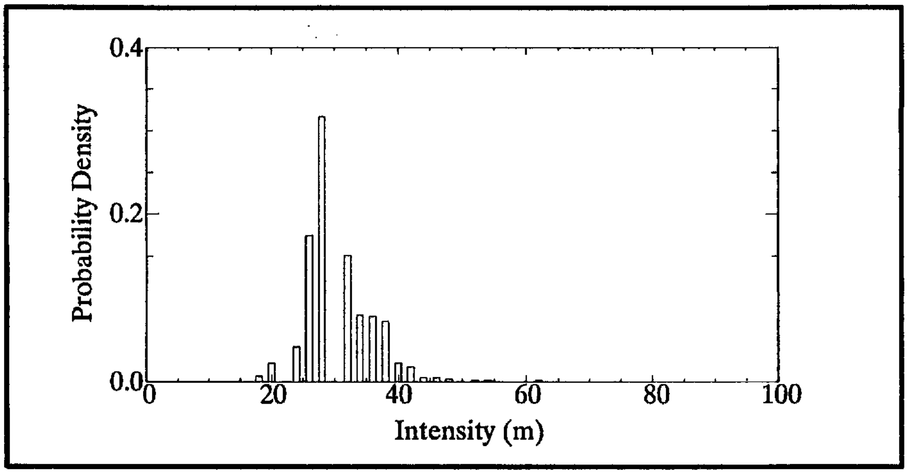

Figure 3. Green Intensity Distribution for the City Target (Macro-pixel 3,3).

The total change of entropy for the dynamic targets was calculated in much the same way. The video segment was digitized at one frame per second. The spatial term of Equation 2 was computed exactly as it was for the static frames. The second term, however, was computed from differences between adjacent, 1-second frames for each macro-pixel. Or,

$$\frac{\partial S_{ij}}{\partial t} \approx \frac{\Delta S_{ij}(t)}{\Delta t} = \left| \frac{S_{ij}(t + \Delta t) - S_{ij}(t)}{\Delta t} \right|, \tag{4}$$

where Δt is one over the digitizing frame rate. We can see immediately that the dynamic targets will have a larger ΔS than do the static ones because Equation 4 is identically zero for all static targets.

In Lantz, Luke, and May's 1992 experiment, the static targets were digitized from scanned photographs. This difference and its consequence will be discussed below.

AC-Data Analysis

Rank-order analysis in Lantz, Luke, and May's (1994) experiment demonstrated significant evidence for *AC*; however, this procedure does not usually indicate the absolute quality of the *AC*. For example, a response that is a near-perfect description of the target receives a rank of *one*. But a response which is barely matchable to the target may also receive a rank of *one*. Table 1 shows the rating scale that we used to assess the quality of the *AC* responses, regardless of their rank.

To apply this subjective scale to an *AC* trial, an analyst begins with a score of *seven* and determines if the description for that score is correct. If not, then the analyst tries a score of *six* and so on. In this way the scale is traversed from *seven* to *zero* until the score-description seems reasonable for the trial.

For all analyses in the 1992 and 1993 studies, we decided *a priori* to use only the upper half of the rating scale. As the strength of the AC-functioning increases, by definition there is less incorrect information (i.e., noise). In other words, the noise contribution to each score level decreases in some unknown way as the the AC increases. Thus, we limited the noise contribution by using only the upper half of the scale in the analysis.

Table 1.
0-7 Point Assessment Scale

Score	Description
7	Excellent correspondence, including good analytical detail, with essentially no incorrect information
6	Good correspondence with good analytical information and relatively little incorrect information.
5	Good correspondence with unambiguous unique matchable elements, but some incorrect information.
4	Good correspondence with several matchable elements intermixed with incorrect information.
3	Mixture of correct and incorrect elements, but enough of the former to indicate receiver has made contact with the site.
2	Some correct elements, but not sufficient to suggest results beyond chance expectation.
1	Little correspondence.
0	No correspondence.

Anomalous Cognition Experiment – 1992

In Lantz, Luke and May's 1992 experiment there were no significant interactions between target condition (i.e., static vs dynamic) and sender condition (i.e., sender vs no sender); therefore, they combined the data for static targets regardless of the sender condition (i.e., 100 trials). The sum-of-ranks was 265 (i.e., exact sum-of-rank probability of $p \leq 0.007$, effect size = 0.248). The total sum-of-ranks for the dynamic targets was 300 (i.e., $p \leq 0.50$, effect size = 0.000).

Entropy Analysis

To examine the relationship of entropy to *AC*, two analysts independently rated all 100 trials (i.e., 20 each from five receivers) from the static-target sessions using the rating scale shown in Table 1, *post hoc*.* All differences of assignments were verbally resolved, thus the resulting scores represented a reasonable estimate of the visual quality of the *AC* for each trial.

We had specified, in advance, for the correlation with the change of target entropy, we would only use the section of the *post hoc* rating scale that represented definitive, albeit subjective, *AC* contact with the target (i.e., scores four through seven). Figure 4 shows a scatter diagram for the *post hoc* rating and the associated ΔS for the 28 trials with static targets that met this requirement. Shown also is a linear least-squares fit to the data and a Spearman rank-order correlation coefficient ($\varrho = 0.452$, $df = 26$, $t = 2.58$, $p \leq 7.0 \times 10^{-3}$).

This strong correlation suggests that ΔS is an intrinsic property of a static target and that the quality of an *AC* response will be enhanced for targets with large ΔS. It is possible, however, that this correlation might be a result of ΔS and the *post hoc* rating independently correlating with the targets' visual com-

* This was conducted *post hoc* because we did not realize until after the judges completed their blind analysis and had been given feedback on the study outcome that a rating scale is more sensitive than ranking. We used this result to form a hypothesis that we tested in the second study.

plexity. For example, an analyst is able to find more matching elements (i.e., a higher *post hoc* rating) in a visually complex target than in a visually simple one. Similarly, ΔS may be larger for more complex targets. If these hypotheses were true, the correlation shown in Figure 4 would not support the hypothesis that ΔS is an important intrinsic target property for successful *AC*.

To check the validity of the correlation, we used a definition of visual complexity, which was derived from a fuzzy set representation of the target pool. We had previously coded by consensus, 131 different potential target elements for their visual impact on each of the targets in the pool. We assumed that the sigma-count (i.e., the sum of the membership values over all 131 visual elements) for each target is proportional to its visual complexity. A description of the fuzzy set technique and a list of the target elements may be found in May, Utts, Humphrey, Luke, Frivold, and Trask (1990).

The Spearman rank correlation between target complexity and *post hoc* rating was small ($\varrho = 0.041$, $t = 0.407$, $df = 98$, $p \leq 0.342$). On closer inspection this small correlation was not surprising. While it is true that an analyst will find more matchable elements in a complex target, so also are there many elements that do not match. Since the rating scale (i.e., Table 1) is sensitive to correct and incorrect elements, the analyst is not biased by visual complexity.

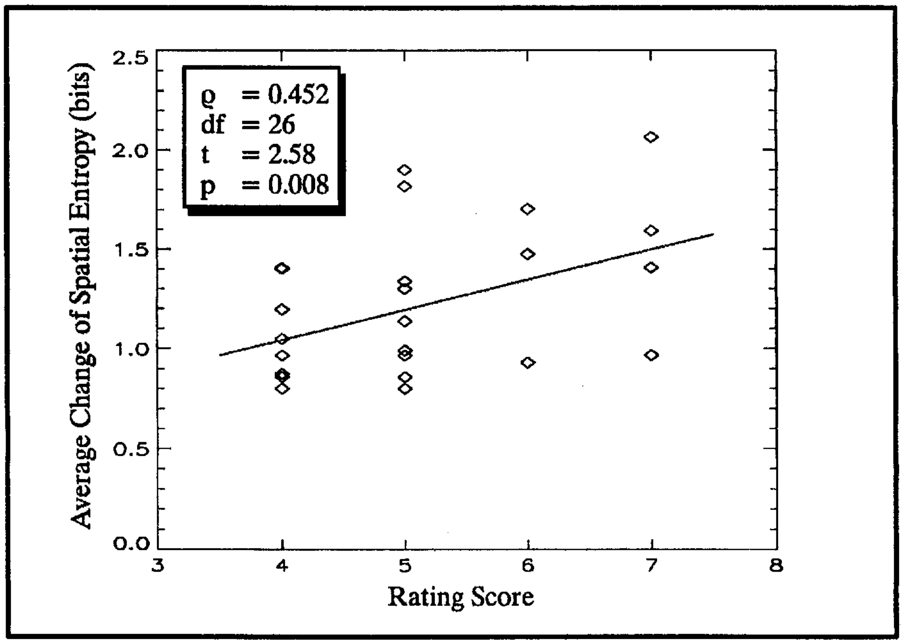

Figure 4. Correlation of *Post Hoc* Score with Static Target ΔS.

Since the change of Shannon entropy is derived from the intensities of the three primary colors (i.e., Equation 1 on page 5) and is unrelated to meaning, which is inherent in the definition of visual complexity, we would not expect a correlation between ΔS and visual complexity. We confirmed this expectation when we found a small correlation ($\varrho = -0.028$, $t = -0.277$, $df = 98$, $p \leq 0.609$).

Visual complexity, therefore, cannot account for the correlation shown in Figure 4; thus, we are able to suggest that the quality of an *AC* response depends upon the spatial information (i.e., change of Shannon entropy) in a static target.

A single analyst scored, *post hoc,* the 100 responses from the dynamic targets using the scale in Table 1. Figure 5 shows the scatter diagram for the *post hoc* scores and the associated ΔS for the 24 trials with a score greater than three for the dynamic targets. We found a Spearman correlation of $\varrho = 0.055$ ($t = 0.258$, $df = 22$ $p \leq 0.399$).

This small correlation is not consistent with the result derived from the static targets; therefore, we examined this case carefully. The total sum of ranks for the dynamic-target case was exactly mean chance expectation, which indicates that no *AC* was observed (Lantz, Luke, and May, 1994). May, Spottiswoode, and James (1994) propose that the lack of *AC* might be because an imbalance of, what they call, the target pool bandwidth. That is, the number of different cognitive elements in the dynamic pool far exceeded that in the static pool. This imbalance was corrected in the 1993 study and is analyzed below. Regardless, we would not expect to see a correlation if there is no evidence of *AC*.

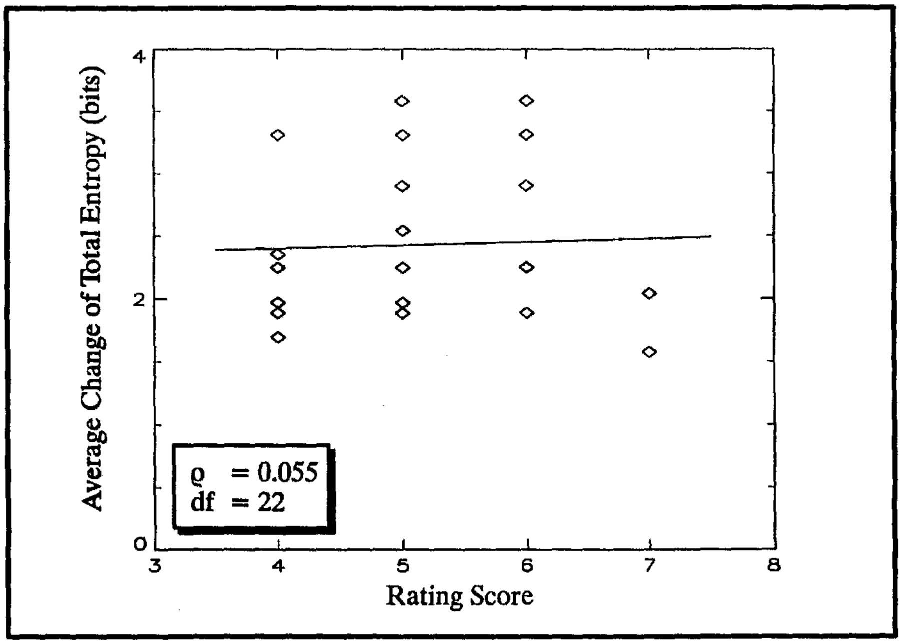

Figure 5. Correlation of *Post Hoc* Score with Dynamic Target ΔS.

Anomalous Cognition Experiment – 1993

The details of the 1993 study may also be found in Lantz, Luke, and May (1994). In that study, they included a static vs dynamic target condition, and all trials were conducted without a sender. They changed the target pools so that their bandwidths were similar. They also included a variety of other methodological improvements, which are not apropos to this discussion.

Lantz, Luke, and May selected a single frame from each dynamic target video clip, which was characteristic of the entire clip, to act as its static equivalent. The static and dynamic targets, therefore, were digitized with the same resolution and could be combined for the correlations.

For each response, a single analyst conducted a blind ranking of five targets—the intended one and four decoys—in the usual way. Lantz, Luke, and May computed effect sizes in the same way as in the 1992 study.

Three receivers individually participated in 10 trials for each target type and a fourth participated in 15 trials per target type. Lantz, Luke, and May reported a total average rank for the static targets of 2.22 for 90 trials for an effect size of 0.566 ($p \leq 7.5 \times 10^{-5}$); the exact same effect size was reported for the dynamic targets.

Entropy Analysis

Differing from the 1992 experiment, an analyst, who was blind to the correct target choice used the scale, which is shown in Table 1, to assess each response to the same target pack that was used in the rank-order analysis. The average total change of Shannon's entropy (i.e., Equation 2) was calculated for each target as described above. Figure 6 shows the correlation of the blind rating score with this gradient. The squares and diamonds indicate the data for static and dynamic targets, respectively.

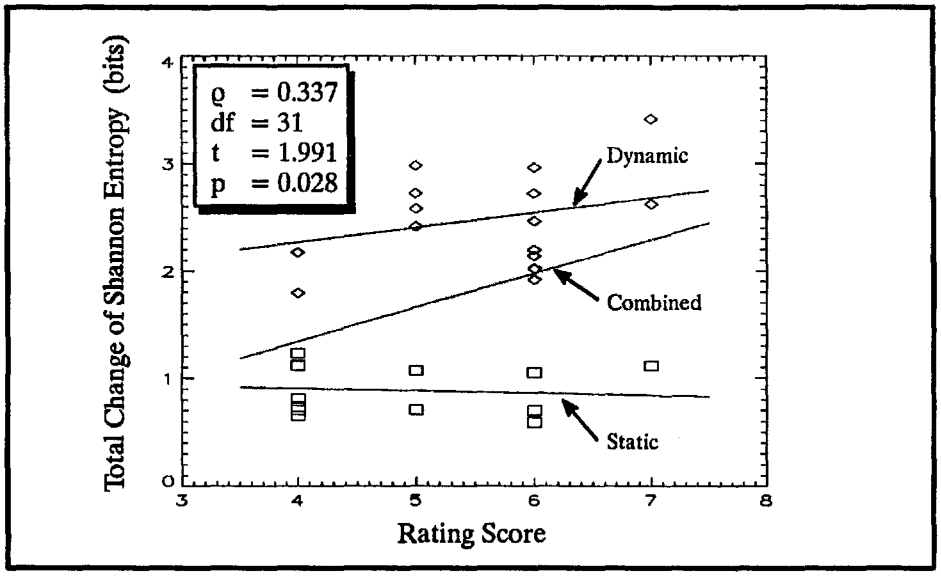

Figure 6. Correlations for Significant Receivers

The key indicates the Spearman correlation for the static and dynamic targets combined. In addition, since the hypothesis was that anomalous cognition would correlate with the total change of the Shannon entropy, Figure 6 only shows the scores in the upper half of the scale in Table 1 for the 70 trials of the three independently significant receivers. The static target correlation was negative ($\varrho = -0.284$, $t = -1.07$, $df = 13$, $p \leq 0.847$) and the correlation from the dynamic targets was positive ($\varrho = 0.320$, $t = 1.35$, $df = 16$ $p \leq 0.098$). The strong correlation for the combined data arises primarily from the entropic difference between the static and dynamic targets. The rating scores were signficantly stronger for the dynamic targets than for the static ones (t=1.71, df=36, p≤0.048).

As a control check for possible unforeseen artifacts, we conducted a monte carlo analysis as follows. The actual blind rating scores greater than three were correlated with the gradient of Shannon's entropy from a target chosen randomly from the pool of the appropriate target type (i.e., only from the static pool or dynamic pool if ratings were originally from a static or dynamic target, respectively). After 100 such monte carlo trials, we found the Spearman rank correlation was $\varrho = -0.0501 \pm 0.311$. If we assume that the standard deviation for the actual data is the same as that in the monte carlo calculation (i.e. $\varrho = 0.337 \pm 0.311$) we find a significant difference between these cross-match controls and the actual data

(t_{diff} = 4.98, $df = 62$, $p \leq 2.68 \times 10^{-6}$). This analysis assumes that the *visual* correspondence between a response and its intended target remains the same, but the gradient of the entropy is random. Thus, it appears that the data correlation does not arise from an artifact.

General Conclusions

To understand the differences between the results in the two experiments, we re-digitized the static set of targets from the 1992 experiment with the same hardware and software that was used in the 1993 study. With this new entropy data, the correlation dropped from a significant 0.452 to 0.298 which is not significant ($t = 1.58$, $df = 26$, $p \leq 0.063$). Combining this data with the static results from the 1993 experiment (i.e., significant receivers) the static correlation was $\varrho = 0.161$ ($t = 1.04$, $df = 41$, $p \leq 0.152$). The correlation for the static targets from the 1992 experiment combined with the significant static and dynamic data from the 1993 experiment was significant ($\varrho = 0.320$, $df = 59$, $t = 2.60$, $p \leq 0.006$). These *post hoc* results are shown in Figure 7. The combined data from the two experiments, including all receivers and all scores greater than four, give a significant correlation ($\varrho = 0.258$, $df = 64$, $t = 2.13$, $p \leq 0.018$).

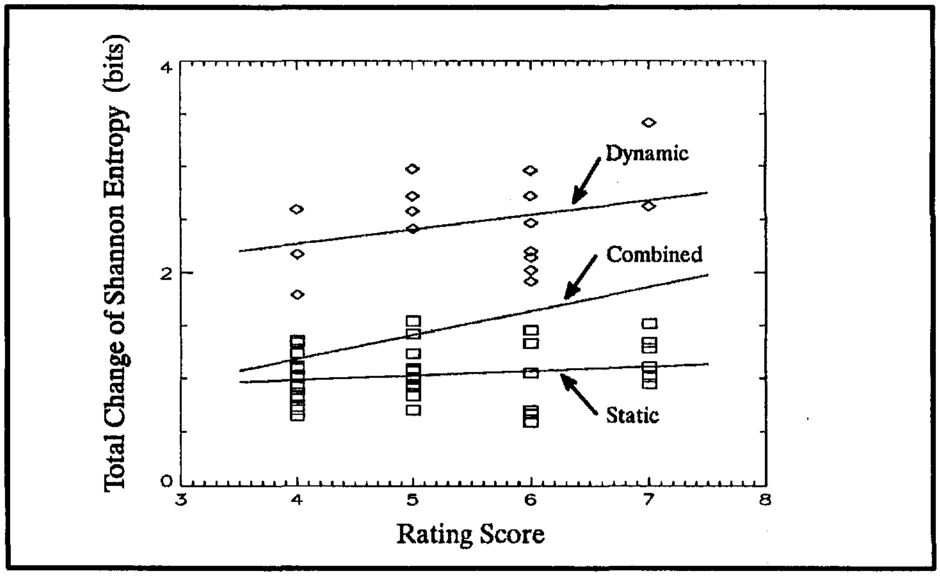

Figure 7. Correlations for Combined Experiments

We conclude that the quality of AC appears to correlate linearly with the average total change of the Shannon entropy, which is an *intrinsic* target property.

These two experiments may raise more questions than they answer. If our conservative approach, which assumes that AC functions similarly to the other sensorial systems, is correct, we would predict that the AC correlation with the frame entropy should be smaller than that for the average total change of the entropy. We computed the total frame entropy from the p_j which we computed from all of the 640×480 pixels. The resulting correlation for the significant receivers in the 1993 experiment was $\varrho = 0.234$ ($t = 1.34$, $df = 31$, $p \leq 0.095$). This correlation is considerably smaller than that from the gradient approach, however, not significantly so. We computed the average of the S_{ij} for the 1,600 macro-pixels as a second way of measuring the spatial entropic variations. We found a significant Spearman's correlation of $\varrho = 0.423$ ($t = 2.60$, $df = 31$ $p \leq 0.007$) for the significant receivers in the 1993 experiment. The difference between the correlation of the quality of the AC with the frame entropy and with either measure of the spatial gradient is not significant; however, these large differences are suggestive of the behavior of other sensorial systems (i.e., an increased sensitivity with change of the input).

We have quoted a number of different correlations under varying circumstances and have labeled these as *post hoc*. For example, hardware limitations in 1992 prevented us from combining those data with the data from 1993. Thus, we recalculated the entropies with the upgraded hardware in 1993 and recomputed the correlations. Our primary conclusions, however, are drawn only from the static results from the 1992 experiment and the confirmation from the combined static and dynamic 1993 results.

Since we observed a significant AC-score difference in the 1993 study, perhaps our correlations with ΔS arise because of some other non-entropy related property such as motion. Yet, the monte carlo results demonstrated that the correlations vanished when the AC-scores were kept constant and random cross-target values were used for ΔS. Because the randomizations were exclusively within target type, the correlation between the AC-scores and ΔS should have remained significant had some non-entropy factor distinguishing static and dynamic targets been operative. In addition, the within-static target ΔS in the 1992 study significantly correlated with the the AC quality.

We conclude that we may have identified an intrinsic target property that correlates with the quality of anomalous cognition. Our results suggest a host of new experiments and analyses before we can come to this conclusion with certainty. For example, suppose we construct a new target pool that is maximized for the gradient of Shannon's entropy yet meets reasonable criteria for the target pool bandwidth. If the Shannon information is important, than we should see exceptionally strong *AC*. We also must improve the absolute measure of *AC*. While dividing our zero-to-seven rating scale in two makes qualitative sense, it was an arbitrary decision. Rank order statistics are not as sensitive to correlations as are absolute measures (Lantz, Luke, and May, 1994); but, perhaps, if the *AC* effect size is significantly increased with a proper target pool, the rank-order correlations will be strong enough. A more sensitive and well-defined rating scale should also improve the analysis. It may be time consuming, however it is also important to understand the dependency of the correlation on the digitizing resolution. In the first experiment, we digitized the hard copy photographs using a flatbed scanner with an internal resolution of 100 dots/inch and used 640×480 pixels for the static and dynamic targets in the second experiment. Why did the correlation drop for the static targets by nearly 35 percent when the digitizing resolution decreased by 20 percent?

We noticed, *post hoc*, that the correlations exhibit large oscillations around zero below the cutoff score of four. If we assume there is a linear relationship between *AC* scores and the total change of Shannon entropy, we would expect unpredictable behavior for the correlation at low scores because they imply chance matches with the target and do not correlate with the entropy.

To determine if we are observing behavioral evidence for receptor-like functioning for the detection of *AC*, we must identify threshold and saturation limits. This can be accomplished if future experiments.

It is absolutely critical to confirm our overall results and to provide answers to some of the enigmas from our experiment. If we have identified an *intrinsic* target property, then all of our research can precede more efficiently. Consider the possibilities if we were able to construct a target pool and eliminate a known source of variance. Psychological and physiological factors would be much easier to detect. Given the availability of inexpensive video digitizing boards for personal computers, replication attempts are easily within the grasp of research groups with modest operating budgets.

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