WHICH SENSOR SET IS BETTER FOR MONITORING SPACE SHUTTLE? A GEOMETRIC ANSWER AND ITS PROBABILISTIC GENERALIZATION

by Matthew Barry[1] and Vladik Kreinovich[2]

[1]Advanced Technology Development
United Space Alliance
600 Gemini
Houston TX 77058-2783
matthew.barry@usahq.unitedspacealliance.com

[2]Department of Computer Science
University of Texas at El Paso
El Paso, TX 79968, USA
email vladik@cs.utep.edu

Abstract. *A Space Shuttle has more than 40,000 sensors; information from these sensors is constantly sent to the Flight Control Center. At the Flight Control Center, there are several automated systems in place which monitor the measurement results. However, in spite of this automatic monitoring, it is useful to have human controllers look at the incoming data; the controllers' expertise can help to make the right decision, especially in non-standard situations.*

A human controller cannot monitor all 40,000 sensors; the experience of space flight shows that a single human controller can monitor at most 200 sensors. With this limitation in mind, the sensors are divided into 200 screens with 200 sensors per screen, so that at any given moment of time, a human controller can select a screen. The problem is: how can we use the statistics gathered from the previous Space Shuttle missions to select the best screen?

In this paper, we first provide a geometric approach to solving this problem, and then show how this geometric approach can be generalized to take statistical information into consideration.

A practical problem: brief description. The control of a Space Shuttle is mostly automatic. A Space Shuttle has more than 40,000 sensors; information from these sensors is constantly sent to the Flight Control Center. At the Flight Control Center, there are several automated systems in place which monitor the measurement results; see, e.g., [Horvitz et al. 1995] and references therein.

In spite of this automatic monitoring and control, it is known to be useful to have human controllers look at the incoming data. The controllers' expertise can help to make the right decision, especially in non-standard situations.

Unlike the computer who can easily monitor all 40,000 sensors, a human controller can monitor at most 200 of them. With this limitation in mind, the sensors are divided into 200 screens with 200 sensors per screen; at any given moment of time, a human controller can select a screen to monitor. Which of these screens is the best to monitor?

To help select a screen, we have, at our disposal, the statistics of almost 100 Space Shuttle missions, with an average of 250 hours per mission. How can we use this information in the selection of the best screen?

Main idea. Our natural idea is to select a screen which would give a human controller the largest *amount of information* about the flight.

In this paper, we will show how this idea can be formalized.

Novice vs. experienced human controllers. Since we are interested in the amount of information that a human controller can get, we will have to distinguish between:

- a *novice* controller to whom most information will be new, and
- an *experienced* controller for whom only the unusual information will be new.

Brief classification of possible situations. We will distinguish between three types of possible situations:

- routine monitoring of a space flight, when the main goal of a human controller is to help make routine planned decisions;
- situations when there is a suspicion that something may malfunction, so the mail goal of the controller is to detect any possible malfunction as soon as possible, and
- situations when a malfunction has already been detected, so we must get as much information about the possible malfunctioning as possible.

Using a natural analogy with street lights, we can mark these situations as, correspondingly, *green*, *yellow*, and *red*. To avoid misunderstanding, we should emphasize that *red* does not necessarily mean catastrophic development: there is a lot of duplication in the Space Shuttle, so it can function well even with a malfunction in, say, one of the computers; however, *red* means that, due to a malfunction, it is necessary to be more cautious about possible decisions.

Geometric approach: brief description. For each sensor, we have an interval of possible measured values, and within this interval, a sub-interval of the desired values. For example, to measure the temperature within the main cabin, we can use a normal room thermometer which can measure a temperature between -60 F and 140 F, with desired values from 60 to 80 (this is just an illustrative example; this is *not* how the temperature is actually measured in the main cabin).

During telemetry, the signal from each sensor is transformed into a binary sequence; if we add 0 and a binary point in front of this sequence, then we can interpret this binary sequence as a real number from the interval $[0, 1]$, so that 0 corresponds to the lowest possible value on the sensor's scale, and 1 corresponds to the largest possible value on this scale. In this interpretation, the desired interval becomes the sub-interval of the interval $[0, 1]$. For example, in the above case, when $[-60, 140]$ is transformed into $[0, 1]$ (the corresponding transformation is $(t + 60)/200$), the sub-interval $[60, 80]$ is transformed into $[0.6, 0.7]$.

After this transformation, the signals $s_1, \ldots, s_N$ corresponding to all $N = 200$ sensors from a given screen form an N-dimensional element $s = (s_1, \ldots, s_N)$ from the set $S = [0,1]^N$. Sequences s in which for each sensor i, the signal fits s_i within the desirable sub-interval D_i forms a *desirable set* $D = D_1 \times \ldots \times D_N$.

Not all possible combinations of signals s_i may have been observed; the actually observed combinations form a set $A \subseteq S$. Of course, in reality, we have observed only finitely many elements from S, but since the measurements are imprecise anyway, observing a vector s means any nearby vector can be the set of actual values of measured quantities; so, we can consider, as A, the set of all the vectors which have actually been observed or which are sufficiently close (within measurement inaccuracy) to the actually observed vectors. The resulting set A is therefore no longer a finite set, but a close domain with an non-empty interior.

Since most archived observations describe proper functioning of all the systems, the set A is either completely within D or at least largely within D.

Green-light situations. In the case of routine monitoring, we can measure the information provided by each screen by the total amount of possible readings on this screen. In geometric terms, this total amount of possible readings is proportional to the (N-dimensional) volume $V(A)$ of the set A of actual reading. Therefore, for green-light situations, we must select a screen for which

$$V(A) \to \max .$$

Yellow-light situations: novice operator. A novice operator know the desired range D, but does not know the actual set A. So, the only way how a novice operator can detect a malfunction is when the observed vector s goes outside the desired set D. Therefore, it is reasonable to select a screen for which this deviation has the highest probability.

If we do not have any information about the frequencies of different possible values of $s \in A$, it is reasonable to consider them equally probable. In this case, the probability $P(A')$ of a situation being in any subset A' of the set A is proportional to the volume $V(A')$ of this set: $P(A') = V(A')/V(A)$. In particular, the probability to detect a malfunction from a given screen is equal to $P(A-D) = V(A-D)/V(A)$. So, we must select a screen for which

$$\frac{V(A-D)}{V(A)} \to \max .$$

Yellow-light situations: experienced operator. An experienced operator not only knows the desired set D, but he also has an intuitive understanding of the actual set A; therefore, he may be able to detect a possible malfunctioning by observing a vector which is still within D but outside A.

In general, we can formalize a malfunctioning as a "random" deviation from the correct state s, i.e., as a transition from a state s to a new state s' which may be different from s. Let ε be the largest possible distance between the original state s and the new state s'. Then, instead of the original state $s \in A$, we get a new state s' from the ε-neighborhood A_ε of the set A.

It may be that the new point is still in A. The probability of detecting a malfunction is therefore equal to the probability of a point from A_ε not to be in A, i.e., to the ratio $V(A_\varepsilon - A)/V(A_\varepsilon)$. For small ε, we know that

$$V(A_\varepsilon) = V(A) + \varepsilon \cdot S(A) + o(\varepsilon),$$

where $S(A)$ is a ($(N-1)$-dimensional) surface area of the domain A. Therefore, for small ε, the probability of detecting a malfunction is proportional to $S(A)/V(A)$. Hence, we should choose a screen for which this ratio is the largest possible:

$$\frac{S(A)}{V(A)} \to \max .$$

In particular, this ratio may be very large in two situations:

- if the area A is itself a (hyper)surface, e.g., a (hyper)plane (then $V(A) = 0$), or
- if A's surface is a fractal (then $S(A) = \infty$).

Red-light situations. In the case when a malfunction has already been detected, we must select a screen which gives the largest information of possible malfunctioning. Sensor readings corresponding to malfunctioning situations form a set $A - D$, so we must choose a screen for which

$$V(A - D) \to \max .$$

Open problems.

1) In order to apply the above geometric ideas to the actual data, we must be able to determine the volume $V(A)$ and the surface are $S(A)$ of the set A from a representative set of points $A' \subseteq A$. It is possible to estimate the volume as a probability of a random point from S being in A (i.e., being close to some point from A'); it is not so clear how to estimate the $(N-1)$-dimensional measure A.
2) Since we will be dealing with an approximation of a set A by some simple geometric shapes, it is also desirable to come up, for different shapes, with reasonable estimates for the above geometric characteristics.

Probabilistic generalizations. In the previous descriptions, we assumed that we only know the set A of possible actual sensor readings, but that the statistics is not sufficient to determine the probabilities of different readings from the set A. If we have enough statistics, then we will be able to determine the probability distribution, e.g., in terms of a probability density function $\rho(s)$ (for probabilistic terms and methods, see, e.g., [Wadsworth 1990]).

In this case, for a green-light situation, we can measure the amount of information by computing the entropy

$$I = -\int \rho(s) \cdot \ln(\rho(s))\, \mathrm{d}s$$

of this probability distribution, and select a screen with the largest possible information content I.

For a yellow-light situation with a novice operator, we shall select a screen with the largest possible detection probability, estimated as $P(A - D) = \int_{A-D} \rho(s)\, \mathrm{d}s$.

Finally, for a red-light situation, we select a screen for which the entropy of the conditional distribution $\rho(s)/P(A-D)$ is the largest possible.

A yellow-light situation with an experienced operator requires a separate analysis. In this situation, we start with a probability density $\rho(s)$ corresponding to the normal behavior. If we then replace the original state s with the modified state s', then we get a new probability distribution $\rho_\varepsilon(s) = \int K_\varepsilon(|\Delta s|) \cdot \rho(s+\Delta s)\,\mathrm{d}s$, where the kernel $K_\varepsilon(|\Delta s|)$ describes the probability of different deviations $\Delta s = s' - s$. Since Δs is small, we can expand the function $\rho(s+\Delta s)$ into Taylor series and only keep linear and quadratic terms in this expansion:

$$\rho(s+\Delta s) = \rho(s) + \rho_{,i} \cdot \Delta s_i + \rho_{,ij} \cdot \Delta s_i \cdot \Delta s_j,$$

where $\rho_{,i}$ denotes a partial derivative with respect to s_i. Then, due to the symmetry of the kernel, the resulting formula becomes $\rho_\varepsilon(s) = \alpha \cdot \rho(s) + \beta \cdot \triangle\rho(s)$. From the normalization condition $\int \rho_\varepsilon(s)\,\mathrm{d}s = 1$, we conclude that $\alpha = 1$, so

$$\rho_\varepsilon(s) = \rho(s) + \beta \cdot \triangle\rho(s). \tag{1}$$

As a measure of relative information, we can use the relative entropy $I = -\int \rho_\varepsilon \cdot \ln(\rho_\varepsilon/\rho)\,\mathrm{d}s$. If we substitute the expression (1) into this formula, then expand the formula in terms of β and keep only linear and quadratic terms, and take into consideration that $\int \triangle\rho\,\mathrm{d}s = 0$, we conclude that I is proportional to

$$I_0 = \int \frac{(\triangle\rho)^2}{\rho}\,\mathrm{d}s. \tag{2}$$

So, we must select a screen for which this characteristic takes the largest possible value.

In particular, if ρ is a Gaussian distribution, then in the coordinates in which s is a sequence of independent Gaussian variables with standard deviation σ_i (i.e., $\rho(s) = \rho_1(s_1) \cdot \ldots \cdot \rho_N(s_N)$), we get

$$\frac{\triangle\rho}{\rho} = \sum_i \frac{\rho_i''(s_i)}{\rho(s_i)} = -\sum \sigma_i^{-2} + \sum s_i^2 \cdot \sigma_i^{-4}.$$

Hence, the integral I is proportional to $\sum \sigma_i^{-4}$, i.e., in terms of the covariance matrix c_{ij}, to the trace of the matrix $\sum_j c_{ij} \cdot c_{jk}$, i.e., to $\sum_{ij} c_{ij}^2$. This formula is true in arbitrary coordinates as well. So, we should select a screen for which this sum takes the largest possible value.

Similar formulas are true if, instead of counting the *amount of information*, we estimate the *probability of detecting* a malfunction m by using Bayes formula. Here, $P(s|m) = \rho_\varepsilon(s)$, $P(s|\neg m) = \rho(s)$, $P_0(m) = p_0$ for some $p_0 > 0$, so we can use Bayes formula to compute $P(m|s)$ and then estimate the probability of detection as $\int P(m|s) \cdot P(s|m)\,\mathrm{d}s$. This probability is proportional to the same integral (2).

For the probabilistic generalization, we face the same *open problem*: how to estimate the screen's characteristics (such as I_0)?

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