System Identification Technique Application to Revealing Human-Operator Skills

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Abstract: A new approach to abnormal situations with regard for the heuristic regularities of human-operator thinking process is proposed. The regularities are revealed on basis of recording the motions of the human-operator eyes over the information field of the control board and processing the experimental data obtained. For data processing, a probability theoretical approach is utilized. Such an approach is based on involving the notion of consistency of measures of dependence of random variables. Within the approach, a set of the so called information correlations has been proposed to serve as a quantitative performance index of human-operator skills.

Keywords: Human factors and errors, Identification, Information correlation, Sampled data, Skills, Stochastic systems

1. STATE OF THE ART AND PROBLEM DESCRIPTION


A unique measure of human attention behavior may be implemented by use of eye tracking. This is particularly important in evaluating present and future environments in which humans do and will work. The examination of human interaction and behavior with their environments, particularly ones in which humans often perform functions critical to safety, is one topic studied by human factors and industrial engineers. Traditional measurement methods of human performance often include measures of reaction time and accuracy, e.g., how fast a person completes a task and how well this task is performed. These are generally measures associated with performance. To study the steps taken to perform the tasks requires analysis of the individual procedures performed. For this analysis, process measures are often required. Eye movements are particularly interesting in this latter context since the present measures which can provide insight into the visual, cognitive, and attentional aspects of human performance (Duchowski, 2007).

In order to disambiguate head movement from eye rotation, multiple ocular features must be measured. Two such features are the corneal reflection (of a light source, usually infra-red) and the pupil center. The corneal reflection of the light source is measured relative to the location of the pupil center. Corneal reflections are known as the Purkinje reflections, or Purkinje images. Due to the construction of the eye, four Purkinje reflections are formed: 1st, reflection from front surface of the cornea; 2nd, reflection from rear surface of the cornea; 3rd, reflection from front surface of the lens; 4th,
reflection from rear surface of the lens being almost the same size and formed in the same plane as the first Purkinje image, but due to change in index of refraction at rear of lens, intensity is less 1% of that of the first Purkinje image. Video-based eye trackers typically locate the first Purkinje image. With appropriate calibration procedures, these eye trackers are capable of measuring a viewer’s Point Of Regard (POR) on a suitable positioned surface on which calibration points are displayed (Duchowski, 2007).

Within the problem outlined, one may state a problem of assessment/identification of industrial plant human-operator skills. Then, within the framework, skills of experienced human-operators will be considered as a basic, i.e. “ideal” with respect to the given plant control task, knowledge.

Corresponding investigation is implemented basing on analysis of the time which is required by the human-operator to make a decision on the plant process behavior using the information provided by detectors distributed over an information/control board. The detectors on the information board are associated in groups in accordance with types of information they provide. These groups are considered as zones. To make a total decision with respect to the plant process behavior, the human-operator has to take certain time to work with a zone, where “time to work with a zone” means the time which the human-operator spends during looking on the zone. In turn, such a time is fixed on basis of the human-operator eye motions by use of the corresponding hardware, the eye trackers. Availability of cheap, fast, accurate and usable eye trackers provides wide range of applications (Clarke, 1998 (and references therein)), Duchowski, 2002, Duchowski et al., 2002, Graeber and Andre, 1999, Tsvetkova, 1999, Vora et al., 2002).

Analysis of the actual human-operator performance algorithm and its deviations from the nominal one enables one to elucidate the general structural features of the decision making process and prove that they are repeatable and stable to various operating conditions. Such an analysis allows one to establish how the structure of decision making varies vs. the complexity of the abnormal situation, its novelty, and the human-operator experience, as well as to reveal hidden human-operator errors made during information collection. In turn, the fact that the structure of the actual human-operator performance algorithm involves characteristics which are independent of the professional and individual distinctions of the human-operator, the complexity and novelty of the abnormal tasks, and the quality of their execution enables one to identify the human factors which must be taken into account to improve the human-machine systems. Studies have demonstrated that the deviations of the human-operator activity from the nominal logical schemes of execution are not occasional or due to their insufficient training, but rather reflect the basic human, heuristic aspects of operational thinking. Along with identifying abnormal disturbances, the activity of the human-operators involves analysis of the state of the entire plant and control system; analysis of the reserves that would assume the load in case of possible disabling of faulty units; prediction of possible variants of accident progression; modeling of the actions to eliminate the given accident and of the variants of its progression; analysis of possible – even improbable – causes of the accident (Tsvetkova, 1999).

The structure of decision making is characterized by concurrent execution of the abnormal situation task, checking that no other accidents occurred at the plant, and clarifying the possibility of driving the plant to the optimal state in the presence of this accident. All these three tasks are executed against the background of repeated checking of the data selected for decision making, the time required by the last two tasks ranging from 30% to 80% of the total time of execution. During the execution, the nominal human-operator performance algorithm is entwined with the actual one; its sequence is violated, and returns are added to it. More importantly, there are no accepted psychological phases of decision making which correlate with the duration of the fixing motions of eyes, such as familiarization, analysis, variant choice, search for a new variant, etc. Upon receiving information about an abnormal situation, the operator immediately hypothesizes about the nature of the accident and checks it (Tsvetkova, 1999). A subtle investigation of human oculomotor system under a challenging search task is presented in (Aks, 2002).

2. ANALYTICAL TOOLS AND MODEL CONSTRUCTING

In accordance with reasoning of the above section, the problem of assessment/identification of human-operator skills is to be considered, from a system theory point of view, as a problem of deriving a model of a mildly formalized system. Consequently, the human-operator model may be considered in terms of system input/output description, with available for observation input and output variables reflecting significant features of the model. Even if no exact analytical model of the input/output relationship between the variables is stated, obviously, there always exists an inherent link which reflects dependence of the output variables from the input ones.

Thus, the above described time which the human-operator spends during looking on each zone \( i \) is considered as a realization of the input variable \( \tau_{\text{zone}(i)} \), while the time required to make a final decision with respect to the plant process behavior is considered as a realization of the output variable \( T_{\text{dec}} \). Within the modeling scheme, for a false decision making, the value of the corresponding decision making time is imposed to be equal to infinity. Finally, \( T_{\text{dec}} \) should be expressed as a function of \( \tau_{\text{zone}(i)}, \ i = 1, ..., N \), where \( N \) stands for the number of zones.

For a stochastic case, a natural way to establish an approximate empirical input/output relationship is using measures of stochastic dependence of random variables. The entity of the approach proposed in the paper is, thus, eliciting the above mentioned inherent link between the (output) variable \( T_{\text{dec}} \) and (input) variables \( \tau_{\text{zone}(i)}, \ i = 1, ..., N \). Such a link, when expressed quantitatively, is to serve to reflect the human-operator skills on the plant process control. Hence, a significant feature of such an approach to human-
operator skills identification is just the choice of an appropriate measure of stochastic dependence between random variables.

Among various measures of dependence, the product correlation is well known and commonly used. However, the ordinary product correlation of random variables \( Y \) and \( X \) may vanish even provided that the random variables are completely dependent, i.e. if there exists a deterministic function \( f(*) \) such that \( Y = f(X) \) with probability 1 (Rajbman, 1981, Rényi, 1959).

Within the paper approach, the basic requirement imposed on a measure of dependence to be used is the measure to be consistent, i.e. (following to Kolmogorov’ terminology) vanishing if and only if the random variables are stochastically independent. In sequel, throughout the paper, the symbols \( \mathbf{M}(\cdot, \cdot) \), \( \mathbf{D}(\cdot, \cdot) \), \( \mathbf{M}[\cdot|\cdot] \), \( \mathbf{D}[\cdot|\cdot] \), and \( \text{cov}(\cdot, \cdot) \) will respectively stand for the mathematical expectation, variance, conditional expectation, conditional variance, and covariance.

In paper of Rényi (1959), seven axioms which are seemed to be the most natural for a measure of dependence \( \mu(X, Y) \) between two random variables \( X \) and \( Y \) has been presented. These are:

A) \( \mu(X, Y) \) is defined for any pair of random variables \( X \) and \( Y \), neither of them being constant with probability 1.

B) \( \mu(X, Y) = \mu(Y, X) \).

C) \( 0 \leq \mu(X, Y) \leq 1 \).

D) \( \mu(X, Y) = 0 \) if and only if \( X \) and \( Y \) are independent.

E) \( \mu(X, Y) = 1 \) if there is a strict dependence between \( X \) and \( Y \), i.e. either \( Y = \phi(X) \) or \( X = \psi(Y) \) where \( \phi \) and \( \psi \) are Borel-measurable functions.

F) If a Borel-measurable functions \( \phi \) and \( \psi \) map the real axis in a one-to-one way onto itself, \( \mu(\phi(X), \psi(Y)) = \mu(X, Y) \).

G) If the joint distribution of \( X \) and \( Y \) is normal, then \( \mu(X, Y) = r_{XY} \), where \( r_{XY} \) is the ordinary correlation coefficient of \( X \) and \( Y \).

Commonly used measures of dependence are the ordinary correlation coefficient, the correlation ratio

\[
\theta(X, Y) = \frac{\mathbf{D}[Y|X]}{\mathbf{D}(Y)}
\]

with nonzero \( \mathbf{D}(Y) \), and the maximal correlation coefficient \( S(X,Y) \)

\[
S(X,Y) = \sup_{\{B\}, \{C\}} \frac{\mathbf{M}[B(Y)C(X)] - \mathbf{M}(B(Y))\mathbf{M}(C(X))}{\sqrt{\mathbf{D}(B(Y))\mathbf{D}(C(X))}},
\]

with \( \mathbf{D}(B(Y)) > 0 \), \( \mathbf{D}(C(X)) > 0 \), and supremum being taken over Borel-measurable functions \( \{B\} \) and \( \{C\} \), and \( B \in \{B\}, C \in \{C\} \).

Among the measures, the only \( S(X,Y) \) has been shown by Rényi (1959) to satisfy all the above axioms, while \( r(X,Y) \) and \( \theta(X,Y) \) do not, in particular axioms D, E, F are not met for the correlation coefficient, and axioms D, F do not for the correlation ratio. However, a significant disadvantage of the maximal correlation coefficient \( S(X,Y) \) is major computational difficulties of its calculation. The problem involves a complicated iterative procedure of finding the first (in modulo) eigenvalue and the first eigenfunctions (corresponding to that eigenvalue) of the stochastic kernel \( p(y, x) / \sqrt{p(y)p(x)} \) (Samaran 1963a, 1963b). Here \( p(x) \), \( p(y) \), \( p(y, x) \), stand for the joint and marginal distribution densities of the random variables \( X \) and \( Y \) correspondingly.

Naturally, the problem is considerably complicated under calculating the maximal correlation coefficient via observed sampled data \( (x_k, y_k) \), \( k = 1,2,... \) of the random variables \( (X,Y) \).

To avoid the disadvantage and simultaneously to use a consistent measure of dependence within the problem, some additional approaches with respect to such a measure of dependence are to be involved. In particular, the following measures of dependence meet the above condition of Kolmogorov imposed on relationship between stochastic independence of the random variables and vanishing a measure of dependence:

- Shannon mutual information

\[
I_{XY} = \mathbf{M} \left[ \ln \left( \frac{p(y, x)}{p(y)p(x)} \right) \right],
\]

- the contingency coefficient

\[
\Delta_{XY}^2 = \mathbf{M} \left[ \frac{(p(y, x) - p(x)p(y))^2}{p(y)p(x)p(y)} \right].
\]

From the point of view of the above axioms of Rényi (1959), the measures \( I_{XY} \) and \( \Delta_{XY}^2 \) do not meet to the majority of them, in particular, they take their values from zero to infinity, but a normalizing transformation may lead to the required results of applicability. Since within the present consideration, the computational issues play an important role, a suitable way of deriving estimates of a measure of dependence is the basic feature of preference to choose the measure.
Namely, the quantity \( t(Y, X) \) proposed by Linfoot (1957) and defined as

\[
t(Y, X) = \sqrt{1 - e^{-2I_{1x}}}
\]  

meets the above axioms A to G for any random variables \( Y \) and \( X \) with non-zero variances. In addition, in contrast to the maximal correlation and contingency coefficient, the measure

\[
\lambda(Y, X) = t^2(Y, X)
\]

based on the \( t(Y, X) \) from (1) will be shown to able effectively calculated using sampled data (Section 3).

Summarizing all these considerations, to describe quantitatively in an objective manner the professional human-operator skills, the set of values

\[
\lambda(T_{dec}, \tau_{zone(i)}), \; i = 1, \ldots, N
\]

calculated in accordance with (1) are chosen. The values in (2) (accompanied a corresponding requirement to the maximally admissible total task execution time) thus represent mathematically the professional human-operator skills with respect to the process control. Obtained in such a manner, the model characteristics, calculated based on data received by observation of experienced human-operator performance algorithm, are suitable to be used within human-operator training evaluation.

A significance of applying namely consistent measures of dependence within the considered problem may be justified by examples when conventional measures of dependence vanish under stochastic dependence between variables.

So, one may consider the following probability distribution density

\[
p_{S,i}(y,x) = \frac{e^{-\frac{x^2+y^2}{2} + \nu \left( \frac{3}{2} e^{-\frac{3}{2}y^2} - 1 - \frac{3}{2} e^{-\frac{3}{2}x^2} - 1 \right)}}{2\pi}, \quad \left| \nu \right| \leq 1,
\]

which belongs to the class of O.V. Sarmanov’s distributions (Kotz et al., 2000). For the density \( p_{S,i}(x,y) \), both ordinary correlation and correlation ration are equal to zero, although the random values are stochastically dependent. The maximal correlation coefficient for the density \( p_{S,i}(x,y) \) is

\[
S(Y, X) = \left( \frac{4}{\sqrt{7}} - 1 \right) |\lambda|.
\]

In Figure 1, the dependence of the values of \( 1 - \exp\left( -2I_{1x}(\nu) \right) \) from (1), corresponding to the density \( p_{S,i}(x,y) \) under various magnitudes of \( \nu \) is graphically presented (solid line) in comparison to the corresponding values of the maximal correlation coefficient (dotted line). As can be seen, for the example the information correlation coefficient demonstrates a high degree of coincidence with the maximal correlation coefficient.

Thus, if for instance, the stochastic dependence between the total decision time and input process, \( \tau_{zone(i)} \) is defined by a distribution density (of course, being not assumed known) of the form \( p_{S,i}(\tau_{zone(i)}, T_{dec}) \) with the parameter \( \nu = \nu_i, \; i = 1, \ldots, n \), then applying conventional, say, correlation methods, to representation of the dependence of the total decision time and “partial” times of looking at the board zones as the identical zero, what is excluded under using the proposed information theoretic approach.

3. ESTIMATING \( \lambda(Y, X) \) BY SAMPLED DATA

Obtaining the coefficients \( \lambda(T_{dec}, \tau_{zone(i)}), \; i = 1, \ldots, N \) in (2) by sampled data may be implemented in various manners relating to estimation of the joint and marginal distribution densities of the (output) variable \( T_{dec} \) and (input) variables \( \tau_{zone(i)}, \; i = 1, \ldots, N \); and Rosenblatt’ (1956b) kernel-type density estimates are commonly used within the problem. Generically, estimating mutual information is implemented via estimation of the corresponding mutual and marginal entropies. As well known, the mutual information \( I_{XY} \) of random values \( Y \) and \( X \) is expressed via their entropies in the following manner:

\[
I_{XY} = H_Y + H_X - H_{YX},
\]

where

\[
H_Y = - \int_{-\infty}^{\infty} (\ln p_Y(y)) p_Y(y) dy,
\]

\[
H_X = - \int_{-\infty}^{\infty} (\ln p_X(x)) p_X(x) dx.
\]
are respectively the marginal and mutual entropies of Y and X. Then, following to approach of Mokkadem (1989), to obtain an estimate \( \hat{X}(Y,X) \) of \( X(Y,X) \) using \( n \) pairs of sampled observations of the random processes \( y(t) \) and \( y(s) \) the following relationships (in general) are natural to be applied (hereafter the super script \( (n) \) will stand for the corresponding estimate of a function over a sample of the length \( n \)):

\[
\hat{X}(Y,X) = 1 - e^{-2H_{XY}^{(n)}} ,
\]

\[
H_{XY}^{(n)} = H_{Y}^{(n)} + H_{X}^{(n)} - H_{XY}^{(n)} ,
\]

\[
H_{Y}^{(n)} = -\frac{1}{h_n} \ln \left( \int_{-\infty}^{\infty} (p_{Y}^{(n)}(y))^{h_n+1} dy \right) ,
\]

\[
H_{X}^{(n)} = -\frac{1}{h_n} \ln \left( \int_{-\infty}^{\infty} (p_{X}^{(n)}(x))^{h_n+1} dx \right) ,
\]

\[
H_{XY}^{(n)} = -\frac{1}{h_n} \ln \left( \int_{-\infty}^{\infty} (p_{XY}^{(n)}(y,x))^{h_n+1} dydx \right) ,
\]

\[
P_{Y}^{(n)}(y) = \frac{1}{n h_n} \sum_{i=1}^{n} K_{j}(y - Y_i) .
\]

\[
P_{X}^{(n)}(x) = \frac{1}{n h_n} \sum_{i=1}^{n} K_{j}(x - X_i) .
\]

\[
P_{XY}^{(n)}(y,x) = \frac{1}{n h_n^2} \sum_{i=1}^{n} K_{j}(y - Y_i) K_{j}(x - X_i) .
\]

In Equations (5) to (10), \( \{h_n\} \) is a sequence of positive real numbers converging to zero; in Equations (8) to (10), \( K_{j}(\cdot) \), \( j = 1, 2 \) are positive bounded kernels on \( \mathbb{R}^s \), and \( Y_i \), \( X_s \) stand for sample values of the random values \( Y \) and \( X \).

Under assumption on \( Y_i \), \( X_s \), \( s = 1, 2, ..., \) to be strongly mixing random processes (Rosenblatt, 1956a), and suitable integrability conditions imposed on the kernels \( K_{j}(\cdot) \), \( j = 1, 2 \), and densities \( p_{X}^{(n)}(y,x) \), \( p_{Y}^{(y)}(y) \), \( p_{X}^{(x)}(x) \) (formulae (3) to (7) of Mokkadem (1989)), estimate (3) has the following mean squared risk

\[
\mathbb{M} \left( \hat{X}(Y,X) - X(Y,X) \right)^2 = O(n^{-1}h_n^4 + h_n^2) .
\]

In turn, due to the inequality

\[
\left(e^{-2a} - e^{-2b}\right)^2 \leq (a-b)^2 , \quad a, b \geq 0
\]

and based on relationship (11), one can conclude that

\[
\mathbb{M} \left( \hat{X}(Y,X) - X(Y,X) \right)^2 = O(n^{-1}h_n^4 + h_n^2) ,
\]

where \( \hat{X}(Y,X) \) is determined by (3).

Thus obtained, the former formulae are applied to obtain sampled estimates of those of (2).

4. CONCLUSIONS

A problem of revealing professional skills of human-operators of complex industrial plants as decision making persons has been considered. Within the problem, an approach based on input/output system identification technique has been proposed, where dependencies of system’s input and output variables are to be investigated. At that, as the variables, the total time of human-operator decision making is considered as the output variable, while times which the human-operator spends during looking on zones of the control board are considered as input variables. A measure of stochastic dependence based, finally, on utilizing the mutual information in the Shannon sense of input and output variables has been motivated to be a suitable quantitative characteristic reflecting the professional human-operator skills. In other words, a “mapping” of (qualitative) human-operator professional skills onto quantitative scale characterized by an information measure of dependence has been proposed. To estimate the measure by use of sampled data, an algorithm converging in mean has been shown to be applicable within the problem statement.

REFERENCES


