Modeling and measuring the interaction between experience and the quality of information

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ABSTRACT: An important application of models of cognitive performance is in determining the effect of changes in information availability on performance in command and control applications. This paper outlines an approach to representing the effect of experience on cognitive performance and describing the interaction with quality of information. Indirect validation of the approach is provided by considering the mean behavior of a group of experimental participants learning a complex laboratory task. The conceptual model is applied in an abstract simulation to investigate the relative importance of reliable, accurate information and experience and it is demonstrated that Fisher’s Information can be used as a consolidated metric that can capture the effects of both sources of variation by describing a mental model in a suitable manner.

1. Background

Analysis of the effectiveness of future information system concepts is central to the development of Network Enabled Capability (NEC) in the UK and Network Centric Warfare (NCW) in the US. It is clearly possible to investigate system concepts empirically using trials involving command teams, although generalizing the results to deducing the performance of a range of system concepts under all conditions is risky. It is desirable that many aspects of the problem can be investigated using constructive modeling, so that the number of concepts that have to be studied empirically is reduced.

There are two aspects of the analysis of system performance: the time taken to achieve an outcome and the quality with which the goal is attained. The consequences of different process implementations in terms of time can be studied using standard discrete event simulation methods. Describing the effect of the same processes on the quality of the decisions that are made is a more challenging problem. There are two distinct sets of effects on decision quality: the impact of variations in information quality and the interaction with the individual making the decisions. Individual decision making is influenced by a number of moderators including training, experience and personality. The aim of the current paper is to describe an approach to representing the variation of the decision maker’s experience and to outline metrics that can measure the interaction between experience and information quality.

1.1 Mental models

The cognitive activity of interpreting information can be considered as applying a model to a set of data and estimating some quantities that provide the basis for interpreting what is happening in the world. For example the set of data may comprise four values \(x_1, x_2, x_3, x_4\) and to determine the state of the world it is necessary to estimate a single linear combination of the values, \(\theta\), given by

\[
\theta = a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4
\]

where \((a_1, a_2, a_3, a_4)\) are model parameters.

If the values of the model parameters are known, the only uncertainty in \(\theta\) arises from the data. If the parameters are unknown, they must be acquired by experience, and uncertainty in the value of \(\theta\) arises from both model and data. The process of acquiring experience in this case comprises estimating the model parameters based on accumulating observations. This process is usually employed in machine learning by applying standard statistical procedures (Mitchell 1997). A bound can be placed on the rate at which estimates of the parameter values can improve with the accumulation of test cases using standard theory of optimal estimation such as Maximum Likelihood.
theory (Kendall & Stuart 1977). This bound can be used to provide an estimate of the likely quality of the estimates of the model parameters at a particular level of experience.

It is argued that this bound can be used to represent the rate at which human experience accumulates, since it is impossible for any system to do better than optimal statistical performance. By applying the law of large numbers, it can be deduced that performance with best training should be proportional to $N^{-1/2}$, where $N$ is the number of exposures.

1.2 Information measures

Shannon’s entropy. Shannon’s information is a measure of the quantity of data (in bits) and this measure is most meaningfully applied to data transactions where there is no change to the data (i.e. communication and transmission of data where there is no model applied to the data). Shannon’s information is given by the following formula:

$$ E = \log_2 n $$

where $n$ is the number of different symbols that can be represented in the code (Shannon 1948). The number of different symbols, $n$, can be calculated as the range of the source divided by the accuracy to which one can determine the value.

Fisher’s information. Fisher’s Information, $I_F$, is defined as the amount of information about a vector of unknown parameters ($\theta$), supplied by the data (Kendall & Stuart 1973) and can be expressed as:

$$ I_F = \frac{1}{\text{Det}(\text{Var}(\theta))} $$

(3)

Fisher’s Information measures ‘goodness of fit’ and so can be treated as a measure of the fusion of the data and model. A problem with using Fisher Information as a measure of ‘goodness of fit’ is that it is dependent on the measurement units. If a parameter is scaled by a factor $f$, $I_F$ is scaled by $1/f^2$. To overcome this problem, we need to use a modified version of Fisher’s Information that is invariant under scale transformations. A form of Fisher’s Information that has this invariance was derived by Cedilnik and Košmelj (Cedilnik & Košmelj 2002):

$$ \text{ModFI} = \frac{1}{2} \log_2 \left( \frac{\prod (b_i - a_i)^2}{\text{Det}(\text{Var}(\theta))} \right)^{-1.79k} $$

(4)

where $b = \text{sup}(\theta)$ and $a = \text{inf}(\theta)$ are the upper and lower bounds of the prescribed range of the parameters and $k$ is the number of parameters. This modified version of Fisher Information will be used in the examples that follow.

Using a combination of modified Fisher’s Information to describe the effect of cognitive activity and Shannon’s Entropy to measure data flow, it is possible to describe information flow in a system that can take account of both failures in information flow and decision-making competence using a common set of metrics.

The approach was applied to an abstract model of a laboratory task that was tested with 60 student volunteers. A pattern matching model of task performance was developed using the observed data. The pattern matching model was then extended to include experience by modeling different numbers of training cases and deriving estimates of the parameters and their variances. The model of the effect of experience was combined with variations in information quality and the metrics were applied to the composite model, providing the means to estimate the relative importance of these two components on the information metrics and task performance.

The trial with the laboratory task is described in Section 2 and the construction of the pattern matching model is outlined. The extension of the model to include experience is described in Section 3 and the results of a simulation trial including experience, data contamination and misapplication of the model are described. The overall findings are discussed in Section 4.

2. Laboratory task

2.1 Introduction

The DECIDE task (Belyavin 2003) was developed as a method of testing how decision making changed with differing training regimes. The task requires both a mental model of how the simulated world works and the use of information sources to monitor the world and choose an appropriate course of action.

The task represents a simple micro-world in which the participant is expected to choose when to start sending troops (up to 50 in a single iteration) through a hostile zone and subsequently when to stop (Figure 2.1 shows a screenshot of the task). Enemy strength varies and this affects the level of casualties suffered by any troops traversing this zone (each enemy causes one casualty in the troops sent). The goal of the participant
is to send the largest number of troops through the hostile zone, while taking a small number of casualties. The two primary performance measures, number of troops successfully transferred (Success) and casualties incurred (Casualties), are combined in a single performance measure \( P \):

\[
P = \frac{\text{Success}^2}{\text{Casualties}}
\] (2)

Four main information sources provide an indication of the level of enemy activity, and participants can choose how to use these sources as a basis for their decisions, although the best indicator of enemy strength is the sum of the four sources.

Initially, the information sources remain hidden as displayed in Figure 2.1 and are revealed only when the participant clicks on a source. Once the participant has made the request, the information remains on the screen for one second before the window closes. Each request is recorded in a data file with the value of the source at the time of the request. Supporting gunfire can be called upon to suppress enemy activity. Each request for gunfire is also recorded in the data file.

There are four primary indicators of enemy strength within the hostile zone and these are described as:

- Sightings from spy planes (ES1);
- Sightings from defectors (ES2);
- Sightings from main base (ES3);
- Intercepted radio-signals (ES4).

In addition to the primary sources of information, the number of troops that have traversed the zone to safety is available. This source provides feedback on the casualty rate the participant is achieving and therefore an indirect indication of enemy strength. However, due to the time taken for the troops to traverse the zone, this feedback is an indication of enemy strength on a previous turn.

The primary information sources are based on four sinusoids with differing frequencies and random initial phases; this can be seen in Figure 2.2. The highest frequency source is ES1 and the lowest is ES4. The sum of the four sinusoids provides the overall level of enemy strength within the hostile zone.

The correlation coefficients of the four underlying sine waves with the enemy strength as follows:

- ES1 (highest frequency): 0.2107;
- ES2: 0.3517;
- ES3: 0.5949;
- ES4 (lowest frequency): 0.7495.

These correlations make it possible to use any combination of information sources to achieve a reasonable performance. The correlations suggest that the best strategies will be based on the lower frequency sources (ES3 and ES4).

### 2.2 Modeling Decision-Making Strategies

Direct recording of information access revealed that each participant chose a selection of the information sources from which to infer the underlying enemy strength. To model the decision-making strategy, the first step is to capture the picture that the participant was looking at before the decisions were made. Similarities between pictures at the point of decision are used to build a statistical pattern-recognition model of the decision-making strategy.

The frequency of use of an information source gives an indication of the participant’s decision-making
strategies. A high request frequency for an information source would suggest an affinity for that source in the decision-making strategy of the participant. A preliminary analysis was used to determine the pattern of use of the sources. It was clear that participants monitored different sub-sets of the information sources at different rates. Based on the preliminary analysis it was concluded that 15 participants did not make sufficient use of the available information to infer what their decision-making process was.

To investigate the remaining 45 individuals’ strategy for choosing a particular course of action, it is important to have a snapshot of the value of the information sources (the data vector) that the individual was monitoring at the decision point.

Each run comprises 100 iterations and the information sources are not monitored every cycle. It is assumed that, if an information source is examined in the recent past, its value will be remembered. After several iterations have passed, the individual is likely to discard the information as out of date and request a new version from which to work. To simulate this behavior, the iterations were grouped into pairs to build the density of data. Each piece of information was time stamped and, if a particular value had not been updated after four iterations (two pairs, equivalent to 24 seconds), then the piece of information was discarded. The rate of change of the four sources was included. This was calculated as the current value of the source minus the last value examined.

Four types of decision occurred in the task:

a. not to send, if currently not sending;

b. to send, if currently not sending;

c. not to stop, if currently sending;

d. to stop, if currently sending.

To model the pattern recognition of the participants, the data vectors they observed at the time of their decisions were collected, and the decisions were assigned to each category. The four categories of decision were then separated into two groups: currently not sending (‘start’) and currently sending troops (‘stop’). Each group therefore has a binary response (e.g. for the start decision: do not send yet (0) and start sending (1)).

A linear discriminant was fitted separately to each of the two decision types. The direction of the discriminant (the values of the coefficients) was calculated using stepwise linear regression. To determine the thresholds for triggering decisions, a simulation of the task was created in the Integrated Performance Modelling Environment (IPME). A screenshot from the model is displayed in Figure 2.3.

The model for each participant and probabilities for examining the information sources were used to approximate the updating of information strategy used by each participant. Gunfire, which could be used to suppress enemy activity, was modeled as a probabilistic decision whilst sending troops. Estimates of the thresholds were then chosen so that the average square root simulated score for each participant matched the square root of the observed performance score.

![Screenshot of the DECIDE model in IPME](image)

A further set of seven participants was removed from the final set because the fit of the thresholds to the observed behavior was inadequate, leaving 38 participants for whom models could be constructed in this way. The model behavior is displayed in Figure 2.4.

Validation of the discriminants was obtained from two sources. The frequency of use was compared to the significant variables in each model and agreement was found. The discriminants were then compared to the information strategy that participants described in a post-trial interview and broad agreement was found.

Using the model form validated for the individual participants, an ‘optimal’ classifier was constructed based on a large number of trials. The performance of this classifier exceeded that of almost all the participants. It was also found that the weights of the different information sources in the optimal classifier were close to the mean weights from the classifiers constructed for the 38 participant models. It is argued that the ‘optimal’ classifier represents pooled experience that exceeds that available to any
individual participant, but the average participant classifier embodies substantial experience and will be closer to the optimum than any individual.

Figure 2.4: a) Observed and b) simulated behavior

3. Metrics: experience and information

As part of a larger study to investigate organizational structure and process, the model of the DECIDE task was generalized to represent information flow in an abstract representation of a tactical headquarters. A simple hierarchical organizational structure was chosen to demonstrate the application of the information metrics.

Data are collected by four intelligence streams. The information from the streams is collated by the planning cell and the ‘picture’ passed to the commander. This process involves the assessment of the quality of the sources and the selection of an appropriate model to underpin the interpretation of the picture. The commander makes a decision based on the picture and the order to send or stop sending is disseminated to the acting agents. Artillery is used to suppress the enemy while troops are being sent.

This structure was complicated enough to provide a meaningful test of the information analysis, yet simple enough to allow a thorough investigation. The overall flow of information in the modeled headquarters is displayed in Figure 3.1.

Each of the intelligence streams collects the data corresponding to a single source in the DECIDE task and these data are transmitted directly to the planning cell without modification. A stream does not pass an observation on every cycle and the data assembled by the planning cell are not necessarily simultaneous and up to date.

The basic structure of the intelligence sources used in the DECIDE task was retained, but the noise that was applied was modified for this study. Four independent Gaussian sources of noise were generated, and linear combinations of these sources constructed so that the variance of the noise on individual sources was large, but that on the sum of the sources was small.

Figure 3.1: Information flow in the organization

A number of information handling failures are observed frequently in studies of organizations and these can be categorized under the following headings:

- **Loss of information.** Items of information are not available when a decision was made. This is frequently caused by temporary communications failure, badly transcribed or transmitted information or system interoperability issues (e.g. information that had to be transferred by hand between two systems).
- **Information corruption.** Items of information can become corrupted during lengthy transmission chains – Chinese whisper syndrome (e.g. “possible enemy formation” becomes “enemy formation” where the latter formation is unambiguously Red while the former may be Blue or Red).
- **Inappropriate model.** The importance of items of information in context is not appreciated correctly on all occasions. This has been interpreted as application of an inappropriate model for the interpretation of the information.
- **Information delay.** Long information handling chains cause information to be late.

The first objective of the study was to demonstrate that these failures can be represented in the model and captured by information metrics. A second objective was to demonstrate that the impact of personal
characteristics such as training and experience can also be reflected in the same metrics.

The model incorporated information loss and corruption mechanisms that affect the value of the third source (ES3), as this source was highly correlated with the underlying enemy strength (i.e. removal of this source should have a high impact on the estimation of enemy strength). The source is either removed for the entire scenario or replaced with a uniformly distributed random number with the same range as the original source.

Information delay is represented by enabling the model to run in one of two states: the decision maker has the most up-to-date observation of the four sources regardless of the time it took for the information to reach him; or the decision maker has delayed information.

The quality of training and experience is represented by reducing the size of the sample of data used to construct the classification model. The use of an inappropriate model is represented through the use of a model that assumes that all the data are sound when the third source is corrupt.

3.1 Information metrics

Shannon’s entropy is used to calculate the flow of data into the system, based on the properties of the data sources. When a source is removed from the scenario, the value of the Shannon Information for that source will be zero. When a source is replaced by random noise the same data are flowing and the same estimate is assumed.

Fisher’s information is used to assess the information content added by fitting models. Two models are fitted at the fusion step in Figure 3.1. To assess whether ES3 is corrupt, a linear estimate of ES3 using ES1, ES2 and ES4 is calculated and compared with the observed value of ES3. The coefficients in the relationship were determined using observations generated by the model. Using the calculated variance of the estimate of ES3 and assuming normality, a simple rejection rule is used to determine whether the observed value of ES3 should be retained. The variance of this estimate of ES3 is used to calculate ModFI for this model.

The next stage in the information flow is the approximation of Enemy Strength (Ens) from the noisy information sources (ES1–ES4) using the approach observed in the DECIDE task. The full model is a linear equation of the form:

\[
Ens = \theta_0 + \theta_1 ES1 + \theta_2 ES2 + \theta_3 ES3 + \theta_4 ES4
\]  

(5)

When it has been decided using the first model that ES3 is corrupt, a reduced model is employed excluding the source.

Fisher’s information for using the model in Equation (5) is a function of the variance of the estimate of Ens. The calculation of this variance is complex as it arises from a number of distinct processes, including the choice of model form. The different processes and sources of variance are described in the remainder of this section.

If the enemy sources, ES1-ES4, are observed without noise, the variance of the estimated Ens is determined by the covariance matrix of \( \theta_0-\theta_4 \). From standard statistical theory, this covariance matrix is a direct function of the training set used to determine these parameters.

If the observations of the enemy sources are not free of noise, there is an additional term in the variance that reflects this source of variation. In practice, there are two sources of variation in the observations of ES1-ES4: direct noise and delay. Bringing together all these effects, the variance in the estimation of Ens comes from three sources:

- the variance in the training data used to fit the model;
- the variance in the incoming data due to noise;
- the variance in the incoming data due to delay.

To represent variations in experience and competence, the parameters were estimated from training sets consisting of 25, 50, 100, 200 and 10000 observations, using standard least squares regression. In each case, the covariance matrix of the model parameters was derived so that it can be applied to the calculation of the variance of Ens for arbitrary values of the data sources.

The covariance matrix of the sources, ES1-ES4, was constructed using a combination of the modeled properties of the sources and the effect of delay, which was determined by simulation of the observation process. The covariance matrix is used in conjunction with the estimates of \( \theta_0-\theta_4 \) to calculate the contribution of noise in ES1-ES4 to the variance of Ens for arbitrary values of the model parameters.

To consider the impact of the information failures on ModFI, and the possible alternative model form the changes in variance must be considered for these
cases. The two types of information failure (i.e. information loss and corruption) both act on information source three (ES3). In the case where the model that is applied to the data is inappropriate (i.e. using a four-source model when ES3 is corrupted or missing) then the following changes to the variance of the incoming data are made:

- the covariance of source three with the other sources is zero, i.e. source three becomes independent of the other sources;
- the variance of the information source changes.

In the case of information corruption the variance of source three is equal to the variance of the uniform distribution from which it is generated.

In the case of the information loss, where the value of ES3 is now set to zero, the variance of the source is equal to the variance of the uniform distribution plus the square of the deviation of the expected value from the true mean of the source. These assumptions imply that the decrease in ModFI is more substantial for the information loss than the information corruption case.

To provide an illustration of the application of the approach, it was demonstrated that the value of ModFI for the estimation of enemy strength depends on the timeliness of the picture. Table 3.1 shows the average value of ModFI for the well trained classification model with and without information delays. It can be seen that delay severely reduces the information content of the decision.

<table>
<thead>
<tr>
<th>Information Delay</th>
<th>Modified Fisher Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>6.82</td>
</tr>
<tr>
<td>Yes</td>
<td>2.09</td>
</tr>
</tbody>
</table>

Table 3.1: Examples of ModFI for the estimation of enemy strength with and without information delays

3.2 Simulation experiment

A simulation experiment was run to investigate the impact of the control parameters listed in Table 3.2. The experiment was fully replicated and 10 replications (runs) per experiment were executed.

The dependent variables for each experiment were:
- Shannon Information for each source;
- ModFI for enemy strength model;
- ModFI for classification model;
- ModFI for information check model;
- task performance.

The analysis was focused on ModFI for enemy strength estimation and task performance as there was more limited variation in the other measures.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Description</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>The number of points in the training set used to calculate the enemy strength estimation model</td>
<td>I. 25</td>
</tr>
<tr>
<td></td>
<td></td>
<td>II. 50</td>
</tr>
<tr>
<td></td>
<td></td>
<td>III. 200</td>
</tr>
<tr>
<td></td>
<td></td>
<td>IV. 10000</td>
</tr>
<tr>
<td>Noise</td>
<td>The noise applied to the incoming data</td>
<td>I. 0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>II. 1.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>III. 1.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>IV. 2.0</td>
</tr>
<tr>
<td>Information Loss</td>
<td>Whether information source three is missing or not</td>
<td>I. Perfect Information</td>
</tr>
<tr>
<td></td>
<td></td>
<td>II. Information Loss</td>
</tr>
<tr>
<td>Information Corruption</td>
<td>Whether information source three is corrupt or not</td>
<td>I. Perfect Information</td>
</tr>
<tr>
<td></td>
<td></td>
<td>II. Information Corruption</td>
</tr>
<tr>
<td>Information Delay</td>
<td>The delay applied to the data</td>
<td>I. No delay</td>
</tr>
<tr>
<td></td>
<td></td>
<td>II. Delay</td>
</tr>
</tbody>
</table>

Table 3.2: Experimental factors

A standard, fixed effects, fully replicated Analysis of Variance (ANOVA) was used to investigate the main effects, and interactions between the control parameters, on ModFI and task performance. The relationship between ModFI and task performance was also examined. A square-root transform was applied to improve the variance properties of the performance measure. An Analysis of Covariance (ANCOVA) was used to determine whether ModFI was a mediating factor in the previous model of task performance against the control factors.

The results of the ANOVA for task performance and ModFI are summarized in Tables 3.3 and 3.4.

<table>
<thead>
<tr>
<th>Factor</th>
<th>d.f.</th>
<th>F Value</th>
<th>P(F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>5, 1728</td>
<td>6.05</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Information Loss</td>
<td>1, 1728</td>
<td>42.0</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Information Corruption</td>
<td>1, 1728</td>
<td>68.26</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Information Delay</td>
<td>1, 1728</td>
<td>99.18</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Info Delay x Info Loss</td>
<td>1, 1728</td>
<td>8.42</td>
<td>0.004</td>
</tr>
<tr>
<td>Training x Info Loss</td>
<td>5, 1728</td>
<td>3.75</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Table 3.3: ANOVA table for the most significant (P(F)<0.01) main effects and interactions for the dependent variable of square root performance
Table 3.4: ANOVA table for the most significant (P(F)<0.01) main effects and interactions for the dependent variable of ModFI

<table>
<thead>
<tr>
<th>Factor</th>
<th>d.f.</th>
<th>F Value</th>
<th>P(F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>5, 1728</td>
<td>2 037.7</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Information Loss</td>
<td>1, 1728</td>
<td>&gt;10 000</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Information Corruption</td>
<td>1, 1728</td>
<td>3 957.9</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Information Delay</td>
<td>1, 1728</td>
<td>&gt;10 000</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Noise</td>
<td>3, 1728</td>
<td>6 158.0</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

ANOVA was used to determine the power of ModFI to explain the variance of the various experimental factors in the analysis of performance. A large reduction in the variance of a particular factor would indicate that ModFI could be used as a substitute measure for this factor. It was found that ModFI explained the majority of the variance of the information delay and the information loss, and a large proportion of the variance of the information corruption factor. ModFI was also able to explain about 50% of the variance of the training effect; therefore ModFI was successful in capturing the main features of training, information failures and information delay. The relationship between performance and ModFI is displayed in Figure 3.2.

Figure 3.2: ModFI used as a predictor for square root performance

\[
\text{Sqrt(Perf)} = 1.63 \times \text{ModFI} + 26.48
\]

\[
R^2 = 0.6085
\]

4. Discussion

A method for modeling experience has been proposed and applied to a complex laboratory task. The model predicts that human training performance should improve with \( N^{-\frac{1}{2}} \), where \( N \) is the number of exposures, a form that corresponds to standard work on training curves. In the trial with the DECIDE task, individual participants had been exposed to between 20 and 50 decisions at the time their performance was measured, corresponding to moderate training. The averaged findings over all participants represent substantial experience, and this is confirmed by the closeness of the mean classifier to optimum performance.

The information analysis framework has been successfully applied to a model of organizational behavior, although there were some drawbacks to the exact techniques used. This indicates that the measures could be applied to real-world systems to define the benefit of both the human and technological elements of the system. The human contribution is measured in terms of the information added to the system by the models applied to the data and the value of quantity and quality of training in the effectiveness of these models. The technological aspects of the system are defined in terms of the volume of data supplied to the system and the accuracy to which these data can be defined.

It was concluded from the analysis reported in Section 3 that the information measures reflected changes in information flow and quality, namely:

- noisy information;
- information loss;
- information corruption;
- time delay.

The measure was also sensitive to the level and quality of training of the models. In addition the information measure could be used to explain a substantial part of the variation of overall performance.

Application of the information analysis is complex in that even in the relatively simple case described in Section 3 there are a number of distinct contributions to the information metrics which need to be identified and calculated. Experience with the approach suggests that a formal method of identifying sources of variance and covariance within the flow is required to make the technique robust and auditable. Conventionally, Data Flow Diagrams (DFDs) are used to describe the data flow and transformation of the data through an organization. To support the systematic application of the information metrics, an evolution of the DFD should be considered so that sources of variance and correlation are highlighted on the same diagram as the definition of information flow.

It is concluded that such a set of measures could be used to analyze C2 systems without necessarily considering the underlying processes within the organization. The information metrics can be applied in the models and analyses of C2 systems in the early stages of assessment, since they are capable of combining effects in the physical and cognitive domains. The approach can be employed to identify
the relative importance of the ‘human’ lines of development regarding manning and training as part of the evolution of NEC.

5. Acknowledgement

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6. References


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CHRIS RYDER is a senior scientist at QinetiQ and has been involved in human performance modeling at the individual, team and organizational level.