Artificial Intelligence Based Approaches to the Effect of Cognitive Style and Physiological Phenomena on Judgmental Time Series Forecasting: A Proposal

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Abstract

Managerial intuition is a well-recognized cognitive ability but still poorly understood for the purpose of developing effective decision support systems. This research investigates whether the differences in accuracy of "time series forecasting" are related to the differences in one`s cognitive style, using statistical test The hypotheses established in the research model did not have positive correlation The lack of correlation between "cognitive style and physiological measures" and accuracy in forecasting may be caused by uncontrolled external variable. Thus, further analyses on physiological characteristics and brainwaves are needed. The approaches such as neural network and data mining are proposed.

1. Introduction

"Judgmental time series forecasting" is prediction of events based on the past data contained in the time series, as opposed to "rational choice," which is formed from causal relationship. Although statistical method is generally utilized in predicting an event, intuitive judgment is also used. Intuitive judgment is used widely since it can be applied in areas where statistical prediction cannot be used; however it is not without potential errors. The main factors that deter the accuracy of "judgmental time series forecasting" have not yet been closely studied. This study investigates whether the differences in accuracy of "time series forecasting" are related to the differences in one's cognitive style. In other words, the way an identical time series are dealt must vary between an analytical person and an intuitive person. The paper makes note of the fact that these cognitive differences influence the accuracy of one's "time series forecast." As of now, there have not been many studies in the cognitive styles and accuracy in "time series forecasting." On the other hand, inaccuracy and errors that can result from relying on intuition can be found in decision-making related literature (Hogarth & Makridakis, 1981; Tversky and Kahneman, 1974).

A human being's brain is divided into left and right halves with each having different functions. The left half deals with the analytical process while the right counterpart handles more emotional and intuitive functions (Stein et al., 1990). Therefore studying the changes in both left and right side of the brain according to one's cognitive style can lead to an interesting discovery. This research is to investigate the accuracy of "time series forecasting" according to one's cognitive style, using statistical test, and proposed the other approaches such as neural network and data mining for deriving the cognitive/physiological characteristics that influence "judgmental time series forecasting."

2. Background

2.1 Cognitive Style in Decision-Making

Singh (1998) demonstrated that the cognitive supporting aids as well as the decision support systems enhanced the effectiveness and the efficiency of decision making.

Through researches on intuitive judgment and cognitive styles, Kuo (1998) discovered that the top economists rely on their keen intuition to aggressively solve their problems. Knowledge necessary for problem solving is dispersed in one's inmost thoughts and environs, which explains why intuition may be able to more effectively solve dynamic and abstract problems. In addition, most of the businesses rely on intuitive forecasting as their main tools in their business activities as more experiments prove that "judgmental forecasting" is more accurate and efficient compared to statistical forecasting (Lim et al., 1998). Ruble and Cosier (1990) studied on effects of cognitive styles and decision setting on performance based on 162 economic-majoring students. Davis, Grove and Knowles (1990) divided 96 graduate students into categories of four decision-making styles and put them through computer-simulation, which situated them in an economic environment. The result confirmed significant differences in cost effectiveness among different decision-making styles. Furthermore, it was discovered that intuitive decision-making was more likely to be used when there is high uncertainty, no past data or experience is available, many variables are scientifically unpredictable, there is time constraint, or many alternatives exist (Agor, 1986).

2.2 Physiological Approaches for Cognitive Task

EEG provides the necessary information on essences of cognitive styles (Wilson and Fisher, 1995). Although identical information may be given, each person processes it differently using different parts of the brain, according to their cognitive styles. In general, analytical person emits less alpha wave in all parts of the brain compared to his holistic counterpart (Riding, Glass, Buttler and Pleydell-Pearce, 1997).

In order to examine the areas of the brain human uses in "judgmental time series forecasting," he controlled the environment to stimulate auditory, visual, and olfactory senses, and prepared scenarios to induce desired emotions. EEG and GSR were measured from laryngitis and frontal lobe to study the effects that emotion played on the brain, and the result confirmed that one was able to forecast more accurately when feeling was negative as opposed to positive feeling.

3. Research Model and Hypotheses

The following study examines the correlation between cognitive styles and physiological characteristics, and their final outcomes.

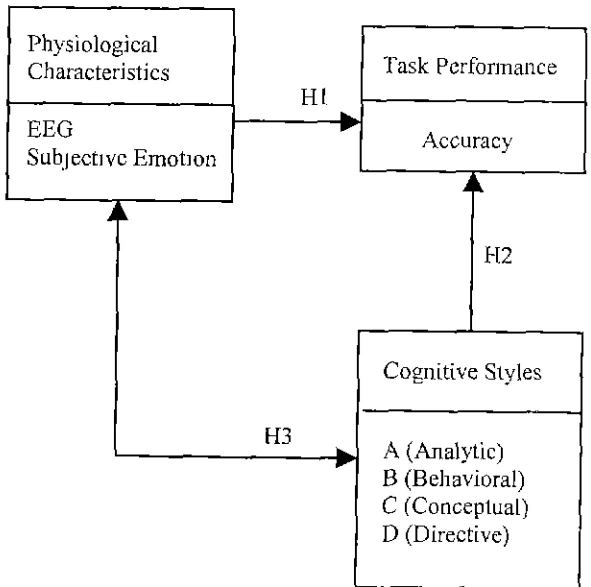

Figure 1 Research Model

The following hypotheses can be constructed using the above model as a basis.

H1: There is no correlation between accuracy in "judgmental time series forecasting" and brain waves.

H2: Accuracy in "time series forecasting" differs among different cognitive styles.

H3: Differences exist in brain waves among different cognitive styles.

In the next section, hypotheses H1 and H2 will be further analyzed to see how the quality of decision is affected by the characteristics of the decision-maker. Hypothesis H3 will be analyzed as the relationship between cognitive style and characteristics of physiological response is further examined.

4. Research Methodology

4.1 Experiment Design

To carefully examine the above model, the following experiment was prepared. IT junior and senior undergraduate students and graduate students were used as test subjects. The subjects have taken decision-making related classes in the past. They were physically fit so as to prevent distortion in physiological signals. We first evaluated cognitive styles of 29 students, and measured their forecasting error Then we added 48 students to get enough number of students for each cognitive style. Hence, the total number of subjects was 77.

The experiment was on time-series forecasting. Time-series data was derived from M-Competition (Makridakis et al., 1996). More precisely, the time-series data given to the test subjects was number of PCs sold in a month and they were to assume that they were PC sales managers. Total of forty data were given which was the sales volume for each month for the period of three years and four months. They were asked to predict the sales volume for next eight months. No other data, such as cause-and-effect data were not provided except for the given times-series data. Consequently, the differences of two cognitive styles-- analytical and intuitive-- were to be decided solely on their ability to solve the time-series problem.

Experiment was carried out individually to measure his/her physiological signals. In order to minimize variance in experiment, one person performed the entire test while standardizing the instruction given for all subjects. To classify subjects' decision style, we used Alan Rowe's Decision Style Inventory derived form the work of noted psychiatrist Carl Jung. Physiological characteristics were analyzed by EEG, while of the many brain waves, alpha and beta waves were examined since they are closely linked to problem solving. Quality of decision-making is defined as accuracy in decision making and accuracy in forecasting the given test. Process of experiment is as follows:

(1) Read the instruction when the subject enters the room.
(2) The researcher gives a brief summary of the experiment.
(3) Prior to the experiment, measure subject's subjective emotion. Measuring subjective emotion in advance is to prevent distortion in controlled environment that may arise due to differences in subjects' emotion prior to the experiment.
(4) Collect the subjective emotion survey and attach transference to the body for measuring brain waves.
(5) Make the subject close his eyes and meditate in a comfortable position with clear mind (2 min.).
(6) Measure the brain wave while having the subject in resting position (1 min.).
(7) Have the subject open his/her eyes and proceed with test (app. 1 min.).
(8) End the test. Measure his/her subjective emotion by giving the survey. Measure subject's cognitive style, which is the only independent variable of the research.

4.2 Measures and Observation

4.2.1 Independent Variable

In this research, we adopted the decision style classification scheme, which is the basis for many measures of decision style including the popular Myers-Briggs Type Indicator test (Myers, 1962). And we used Alan Rowe's Decision Style Inventory to measure the subjects' decision styles such as A (analytic), B (behavioral), C (conceptual), and D (Directive) (Rowe and Boulgarides, 1994).

4.2.2 Dependent Variable

The following experiment measures accuracy, physiological measures, and subjective emotion.

Accuracy: Accuracy of time-series forecasting is measured by MAPE(Mean Absolute Percentage Error). MAPE is a universally used tool in time-series forecasting and represented in absolute percentage value of standard deviation of forecasted value from actual value.

Physiological measures: This experiment measures the EEG to discover physiological responses related to decision-making. Alpha and Beta, the main brainwaves, are analyzed.

Subjective Emotion: A subject's emotion is measure using five-point Lickert scale.

5. Statistical Results

T test and ANOVA were used for the results of this experiment. For statistical package, SPSS for Windows (v. 9.0) was used.

Results of analysis is as follows:

(1) Correlation between accuracy in time-series forecasting and brainwaves was not found.
(2) No differences exist in accuracy of time-series forecasting between different cognitive styles. The differences within the cognitive style were comparatively large; therefore, the difference between the groups was hard to see.
(3) According to the cognitive style, brain waves of left and right halves of the brain have the tendency to concentrate in one side of the brain.

The lack of correlation between "cognitive style and physiological measures" and accuracy in forecasting may be caused by uncontrolled external variable. Further analysis on characteristics of physiological response and brainwaves are needed.

6. Artificial Intelligence based Approaches

The hypotheses established in the research model did not have positive correlation. However further research is possible if artificial neural network and data-mining technologies can be utilized. Following method is suggested where an artificial neural network is used to determine the degree of correlation among many parameters. In this analysis, Self-organizing neural network , which is representative of SONN.

Secondly, data mining technology can be used. This research analyzes in various ways by using cognitive style data and characteristics of physiological response to discover which positively influence intuitive forecasting. Using data mining technology, previously established hypotheses are confirmed as well as to automatically explore other existing rules. By doing so, database can be created by categorizing research data and find systematic relationship from it. Discovered rules are then verified using statistical hypotheses verification method or neural network technology.

6.1 Self-Organizing Neural Network

We propose a non-traditional method to analyze the effect of cognitive style of decision-makers on the accuracy of intuitive time-series forecasting. We use the self-supervised adaptive algorithm (Luttrell, 1992) to find out any correlation between them

6.1.1 Self-Supervised Adaptive Neural Network

Self-organizing neural network, a competitive network, extracts features in input samples by usually projecting input vectors from a space of higher dimensions into a space of lower dimensions (Kohonen, 1995). Self-organizing algorithm updates not only the weight vector of the winning neuron in the self-organizing layer but also those of its neighboring neurons. With this training scheme, neighboring neurons would become to respond similarly to a specific input vector.

When the training is completed successfully, we may expect that the weight vectors of neighboring neurons constitute prototypes for a certain class. That means the distribution of winning neurons for a class may be distinguished from the distributions of winning neurons' groups of other classes.

Luttrell proposed self-supervised adaptive neural network (Luttrell, 1992), which is a SONN and inherently uses the correlation between input vectors of separate clusters. The self-supervised adaptive algorithm achieves the ability by updating the weight vectors of neurons in a cluster using the information of the training status of the other clusters. He uses the information to determine the shape of the neighborhood function. In the self-supervised adaptive algorithm the neighborhood function is not necessarily symmetric, which constitutes the most important difference from the conventional SONNs. And the degree of correlation between input vectors of separate clusters affect the performance of the network (Luttrell, 1992). Actually with the self-supervised adaptive algorithm, we could obtain better forecasting performance in power load forecasting problem than other much more complicated models (Yoo et al., 1999).

6.1.2 The Structure of the Self-Supervised Adaptive Neural Network

We use two clusters of neurons in the self-supervised layer and deploy neurons in one dimension for each cluster. The cognitive styles form the input vector to the first cluster, and the forecasting error becomes the input to the other cluster.

Hence, we use four-dimensional input vector for the first cluster. Each input element corresponds to A, B, C, and D cognitive styles, respectively. When the student belong to class A, 0.8 is assigned to the first element and 0.2 to the rest. The input vector to the second cluster has one element, which is the forecasting error. However, the number of neurons for each cluster is the same and large enough (at least two times the number of classes for the input vectors for the first cluster).

During the training, we accumulate and store the output (i.e., feature value) of each neuron for each pattern.

6.1.3 Discriminant Analysis

After the training, we use the histograms of the accumulated feature values of neurons to obtain the scatter matrices for discriminant analysis of statistics (Fukunaga, 1990) to eventually figure out the relative correlation degrees between the cognitive styles and the error of intuitive time-series forecasting.

During the training we accumulate feature values of each neuron for each pattern in the array

$$F_{p,g,n}$$

where the subscripts p, g and n are indices of patterns, clusters, and neurons, respectively. Then we store the accumulated feature values of neurons for each class (or cognitive style) in the array

$$FC^{c}_{g,n} = \sum_{p=1}^{NP(c)} F_{p,g,n}$$

for patterns in class c (3.1)

where $NP(c)$ = number of patterns in class c. The average of the histogram values of neurons for each class is stored in the array

$$FCM^{c}_{g,n} = \frac{1}{NP(c)} FC^{c}_{g,n}$$

for patterns in class c (3.2)

The two arrays in Eqs. 3.1 and 3.2 reflect the sensitivity of neurons to each class.

To find out how differently the neurons respond to different classes by using the mean feature values, we compute the discriminant array shown in Eq. 3.3.

$$FD^{c1,c2}_{g} = \sum_{n=1}^{N} | FCM^{c1}_{g,n} - FCM^{c2}_{g,n} | \tag{3.3}$$

where $c1$ and $c2$ are the indices for classes and N stands for the number of neurons in each cluster. This matrix is zero-diagonal and symmetric. The average of discriminant feature over clusters is stored in the array

$$FDM^{c1,c2} = \frac{1}{NG} \sum_{g=1}^{NG} FD^{c1,c2}_{g} \tag{3.4}$$

where NG stands for the number of neuron clusters in the network.

The average of discriminant feature over clusters and classes is stored in the array

$$FDM^{c} = \frac{1}{NC} \sum_{c2=1}^{NC} FDM^{c,c2} \tag{3.5}$$

which shows the distinctness of each class. The average of discriminant feature over class and comparing class is computed and stored in the array

$$FDM_{g} = \frac{1}{NC^2} \sum_{c1=1}^{NC} \sum_{c2=1}^{NC} FD^{c1,c2}_{g} \tag{3.6}$$

which shows the performance of each cluster.

For class c, we can compute

$$\begin{aligned} & E\{(\mathbf{X}-\mathbf{M}_c)(\mathbf{X}-\mathbf{M}_c)^T \mid \omega_c\} \\ = & \sum_{p=1}^{P_c} (\mathbf{x}_p-\mathbf{M}_c)(\mathbf{x}_p-\mathbf{M}_c)^T \end{aligned} \tag{3.7}$$

where $\mathbf{x}_p$, $\mathbf{M}_c$, and P_c stand for the feature vector, class mean feature vector, and the number of feature vectors in class c, respectively. In a cluster, the diagonal elements show the squared distance between feature vectors

$$F_{p.g,n}$$

and class mean feature vectors

$$FCM^{c}_{g,n}.$$

We assign an array for this matrix as

$$FS^{c}_{g,n1,n2}.$$

To show the scatter of samples around their class expected vector, we use the measure

$$S_w = \sum_{c=1}^{NC} p(\omega_c)\, E\{(\mathbf{X}-\mathbf{M}_c)(\mathbf{X}-\mathbf{M}_c)^T \mid \omega_c\}$$

$$= \frac{1}{NP}\sum_{c=1}^{NC}\sum_{p=1}^{NP(c)} (\mathbf{x}_p-\mathbf{M}_c)(\mathbf{x}_p-\mathbf{M}_c)^T \quad (3.8)$$

where *NP* stands for the total number of patterns, *NP(c)* stands for the number of patterns in class *c* and *NC* stands for the number of classes. This measure corresponds to the average of the array feature scatter over classes. We assign an array for this within-class feature scatter matrix as

$$FSW_{g,n1,n2}$$

We use a measure for the scatter of class mean feature vectors as in Eq. 3.9.

$$S_b = \sum_{c=1}^{NC} p(\omega_c)\,(\mathbf{M}_c-\mathbf{M})\,(\mathbf{M}_c-\mathbf{M})^T$$

where

$$\mathbf{M} = E\{\mathbf{X}\} = \sum_{c=1}^{NC} p(\omega_c)\,\mathbf{M}_c. \quad (3.9)$$

We declare an array to store the results of the formula (between-class feature scatter) as

$$FSB_{g,n1,n2}.$$

Finally, we use a J-measure

$$tr(S_w^{-1} S_b) \quad (3.10)$$

to formulate criteria for class separability. It is larger when the between-class scatter is larger or the within-class scatter is smaller.

We can repeat the simulation with subjective emotions and physical phenomena instead of the cognitive styles. Then, by using the results of Eq. 3.10 from the three different simulations, we can compare the correlation degrees between each of the three parameters and the forecasting error.

We expect that using the self-supervised adaptive neural network is advantageous over using the conventional self-organizing neural network in figuring out the correlation degrees between input vectors of separate clusters, since the self-supervised adaptive network can inherently use the correlation between them, and its performance is proportional to the degree of the correlation [Luttrell, 1992].

6.2 Data Mining Approach

Data mining is finding hidden rules in given dataset using non-traditional methods (Agrawal, Imielinski, and Swami, 1993; Chen, Han, and Yu, 1996; Frawley, Shapiro, and Matheus, 1991). The objective is to discover some useful tendency or patterns from the given collection of data. We had mined the rules representing the effect of cognitive style, subjective emotion, and physiological phenomena on the accuracy of subjects' judgmental time-series forecasting. Then we have tried to find out any consistent tendencies in the frequent rules.

6.2.1 Preparation for Data Mining

For each subject, we have 1 style value (A, B, C, or D), 8 (original) subjective emotion values (in numeric), 8 (original) EEC values (in numeric), and 1 MAPE value (in numeric). In addition, we made some derived (statistical) values (in numeric) from original emotion data and EEG data for more macroscopic analysis:

- The increasing ratio of positive-stressed values between before- and after-forecasting,
- The increasing ratio of positive-relaxed values,
- The increasing ratio of negative-stressed values,
- The increasing ratio of negative-relaxed values,
- The increasing ratio of left-alpha EEG values between before- and during forecasting,

- The increasing ratio of left-beta EEG values,
- The increasing ratio of right-alpha EEG values,
- The increasing ratio of right-beta EEG values,
- Total volume of left EEG before forecasting,
- Total volume of left EEG during forecasting,
- The increasing ratio of left EEG,
- Total volume of right EEG before forecasting,
- Total volume of right EEG during forecasting,
- The increasing ratio of right EEG,
- Total volume of alpha EEG before forecasting,
- Total volume of alpha EEG during forecasting,
- The increasing ratio of alpha EEG,
- Total volume of beta EEG before forecasting,
- Total volume of beta EEG during forecasting,
- The increasing ratio of beta EEG,
- Total volume of EEG before forecasting,
- Total volume of EEG during forecasting, and
- The increasing ratio of EEG.

Data mining requires partitioning every continuous (numeric) value range into several zones. We partitioned all the numeric properties into three levels: *high*, *low*, and *middle*. Highest 30% was assigned to 'high'; Lowest 30% was assigned to 'low'; and the rest 40% was assigned to 'middle'. Thus 23 of 77 MAPE values were 'high', 31 of 77 MAPE values were 'middle', and 23 of 77 MAPE values were said to be 'low'. The same values at any boundary were considered to be 'middle.'

6.2.2 The Mining Results

So far, we have found so many rules (relationships) between arbitrary pair of properties. Infrequent rules were removed and we tried to find out any consistent tendencies in the rest frequent rules. The rest of this section consists of our observations. The portions of high accuracy (low MAPE), middle accuracy (middle MAPE), and low accuracy (high MAPE) will be written in this order in '(' and ')' at the end of any tendencies or rules.

Observations on the Effect of Cognitive Style

Observation 1: The subjects in style A had a tendency to make high accurate (low MAPE) forecasting *(10/25, 9/25, 6/25)*

Observation 2: The subjects in style B had a tendency to make low accurate forecasting *(3/17, 8/17, 6/17)*.

And we can't find any meaningful tendencies in style C *(7/23, 9/23, 7/23)* and style D *(3/12, 5/12, 4/12)*.

Observations on the Effect of Subjective Emotion

Observation 3: There was a tendency that regardless of positive or negative emotion, the higher relaxed level the subject shows at before-forecasting, the higher accuracy (s)he achieves, and when the lower relaxed level is shown, the lower accuracy is achieved. The evidence is:

- negative-relaxed-before-forecasting (*low*)

-> *(4/11, 1/11, 6/11)*

- positive-relaxed-before-forecasting (*mid*)

-> *(5/22, 9/22, 8/22)*

- positive-relaxed-before-forecasting (*high*)

-> *(6/12, 3/12, 3/12)*

Observation 4: In contrast, there was a tendency that regardless of positive or negative emotion, the higher stressed level the subject shows at before-forecasting, the lower accuracy (s)he achieves, and when the lower stressed level is shown, the higher accuracy is achieved. The evidence is:

- negative-stressed-before-forecasting (*high*)

-> *(3/12, 4/12, 5/12)*

- positive-stressed-before-forecasting (*low*)

-> *(5/11, 4/11, 2/11)*

- positive-stressed-before-forecasting (*high*)

-> *(2/10, 3/10, 5/10)*

Observation 5: There was a tendency that regardless of stressed or relaxed, the higher positive level the subject shows at after-forecasting, the higher accuracy (s)he achieves, and when the lower positive level is shown, the lower accuracy is achieved. The evidence is:

- positive-stressed-after-forecasting (*low*)

-> *(3/15, 7/15, 5/15)*

- positive-stressed-after-forecasting (*mid*)

-> *(7/18, 7/18, 4/18)*

- positive-relaxed-after-forecasting (*low*)

-> *(3/16, 6/16, 7/16)*

- positive-relaxed-after-forecasting (*mid*)

-> *(7/17, 8/17, 2/17)*

Observation 6: And, there was a tendency that regardless of stressed or relaxed, when the subject shows high or low negative level at after-forecasting, (s)he would achieved high or low accuracy, and when the level is middle, the accuracy is middle, too. The evidence is:

- negative-stressed-after-forecasting (*low*)

-> *(5/13, 3/13, 5/13)*

- negative-stressed-after-forecasting (*high*)

-> *(3/12, 6/12, 3/12)*

- negative-relaxed-after-forecasting (*low*)

-> *(5/13, 2/13, 6/13)*

- negative-relaxed-after-forecasting (*high*)

-> *(6/16, 4/16, 6/16)*

- negative-relaxed-after-forecasting (*mid*)

-> *(4/19, 12/19, 3/19)*

The tendencies in the Observation 5 and 6 may come from the fact that when a subject is confident of his(her) decision just before, (s)he feels happy; and when (s)he is diffident of his(her) decision just before, (s)he feels unhappy.

Observations on the Effect of Physiological Phenomena

Observation 7: There was a slight tendency that the accuracy is low when the total volume of EEG at before-forecasting is low *(7/23, 7/23, 9/23)*.

But there was no evidence that the accuracy is high when the total volume of EEG at before-forecasting is high *(6/23, 11/23, 6/23)*

Observation 8: There was a slight tendency that the accuracy is low when the total volume of EEG at during-forecasting is low (6/23, 8/23, 9/23), and the accuracy is low when the total volume of EEG at before-forecasting is low *(7/23, 11/23, 5/23)*.

From the Observation 7 and 8, we can't find any distinct tendency between total volume of EEG and the accuracy.

Observation 9. There was a tendency that the accuracy is low when the total beta volume at before-forecasting is low *(7/23, 7/23, 9/23)*, and the accuracy is high when the total beta volume at before-forecasting is middle *(11/31, 12/31, 8/31)*.

But we can't find the effect of 'high' total beta volume at before-forecasting on the accuracy *(6/23, 11/23, 6/23)*

Observation 10: There was a tendency that the accuracy is high when the increasing ratio of beta is low (i.e., when beta decreases) *(7/23, 11/23, 5/23)* or high (i.e., when beta increase significantly) *(9/23, 7/23, 7/23)*, and the accuracy is low when the increasing ratio of beta is middle (i.e., when beta is relatively invariant) *(7/31, 13/31, 11/31)*

From the Observation 9 and 10, we can find the fact that the effect of beta rhythm on the accuracy is true.

Observation 11: There was a tendency that the accuracy is low when the left EEG (alpha + beta) volume at during-forecasting is low *(6/23, 8/23, 9/23)*, and the accuracy is high when the left EEG volume at during-forecasting is middle *(11/31, 12/31, 8/31)*.

But we can't find the effect of 'high' total EEG volume from the left-brain at during-forecasting on the accuracy *(6/23, 11/23, 6/23)*.

Observation 12: There was a tendency that the accuracy is high when the increasing ratio of left EEG is low (i.e., when the left EEG decreases) *(9/23, 8/23, 6/23)* or high (i.e., when the left EEG increase significantly) *(8/23, 10/23, 5/23)*, and the accuracy is low when the increasing ratio of left EEG is middle (i.e., when the left EEG is relatively invariant) *(6/31, 13/31, 12/31)*.

From the Observation 11 and 12, we can find the fact that the effect of EEG from the left-brain lobe on the accuracy is true.

6.2.3 Discussion

Subjects in style A (Analytic) seem to be more accurate, and subjects in style B (Behavioral) seem to be less accurate. It means that if we hire analysts in style A, we would have more opportunity to be happy.

Subjects in relaxed mode seem to be more accurate. It means that if we make our analysts relaxed, we would have more opportunity to be happy.

Subjects' left EEG and beta rhythm seem to have a significant effect on their forecasting accuracy. It means that if we can control our analysts' left EEG and beta signal, we would have more opportunity to be happy.

The effect of subjective emotion and physiological phenomena on the accuracy of style A (or B) subject's forecasting, the effect of cognitive style and physiological phenomena on the accuracy of relaxed (or stressed) subject's forecasting, and the effect of cognitive style and subjective emotion on the control over left EEG and beta signal are much worth analyzing in depth. Moreover, the effect of cognitive style on subjective emotion, the effect of cognitive style on EEG, the effect of subjective emotion on EEG, the effect of EEG on subjective emotion, and accurate subjects' dominant cognitive style, dominant subjective emotion, and dominant EEG signal should be analyzed as well.

7. Conclusion

Most of the psychologists and decision scientists agree that intuition capacity must be supported for important decision making process. However, hardly any previous research has been made where decision makers' intuition capacity is examined. Furthermore, research that includes cognitive physiological elements is even more rare. The significance of this research is to discover cognitive/physiological element that can improve outcome of intuitive forecasting. It is the basic research which can foster the environment for quality decision making, which will further enhance decision support system. In other words, the research assures the first basic technology that combines strong intuition of decision maker with computer analytical capability for establishing research tool of next-generation decision support system.

Subject of next research is as follows: influence of decision maker's cognitive style on the quality of unstructured decision-making; intuition capability of decision maker and physiological/cognitive characteristic research; and cognitive tool for supporting intuition capability of decision maker. Additional research will be carried to bring light to these issues.

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