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# A Dynamic Comparison in Time State Space Models on Identity Psycho-Physiological Response Data

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**Abstract:**

When respondents' skin conductance response and heart rate are measured, the main process focuses not only on the subtle response but rather on the interaction between the person and their environment and information that sheds some light on the human mind processes. Some researchers have started working on ways of integrating physical phenomena to response in physiological processes, such concept includes integrating state-space models to interpret physiological control systems that represent the mechanism of psycho-physiological processes. This paper presents a customised measure by applying state-space models in the prediction of physiological processes and a standard way of interpreting response potentials. Three different state-space models were used and the performance for each model is compared, the result shows that the fourth identified space model (N4SID) is most probable in interpreting physiological response with a performance of 98% focus. This would help in dealing with the choice of the development of physiological control systems in the design of psycho-physiological mechanisms in robotics.



## 1 INTRODUCTION

Current research has discussed the advantages of using physiological measures to understand user cognition and behaviour, such as viewing the mind as having a physical substrate, and psychophysiological measures offer tools for mining information about non-conscious and non-reportable processes of the user mind. It can substantially contribute to the understanding of basic cognitive processes, emotions, and behavioural attributes of a person. One interesting demonstration of physical substrates of emotion is its relation to the concept of the affective blind spot of cognitive processes, where respondents with blind or poor eyesight are unable to report any visual stimuli, but can react reliably to their emotional valence as measured from EEG and fMRI and can even mimic the facial expression that is exposed to them.

Psycho-physiological processes are undoubtedly a broad field where the approaches are carried out with the importance of the methodology and its considerations and also a lot is written literature. The methodology used in this paper introduces the use of control systems to develop a physiological state-space model for the interpretation of user attributes that are subtle and difficult to detect, it uses the basic physiological measuring data from a predefined experiment with Skin conductance response measure (SCR), Skin temperature, Fixation location, Pupillary response and Baseline estimates. The proceeding sections discuss some literature review, methods, and results obtained from the model design.

# 2 LITERATURE REVIEW

The state-space model (SSM) speaks of a class of probabilistic graphical models [5, 22, 14, 7, 28] which defines the probabilistic requirements between the latent state variable and the observed measurement.

A more concise definition is that the state or the measurement can be either continuous or discrete. The state area of control engineering [12, 27, 26, 6, 15], provides a general framework for analysing deterministic and stochastic dynamical systems that are measured or observed through a stochastic process. The SSM framework has been successfully applied in engineering, statistics, computer science, and economics to solve a broad range of dynamical systems problems. Other terms used to describe SSMs are hidden Markov models (HMMs) [11, 24, 1, 10, 25, 30, 2, 3, 31] and latent process models. The most well-studied SSM is the Kalman filter, which defines an optimal algorithm for inferring linear Gaussian systems. An important objective of computational neuroscience is to develop statistical techniques to characterize the dynamic features inherent in neural and behavioural responses of experimental subjects collected during neurophysiological experiments.

In neuroscience experiments, measurements of neural or behavioural data are often dynamic, noisy, and have rich temporal structures. Examples of such include intracellular or extracellular recordings, neuronal spike trains, local field potentials, EEG, MEG, fMRI, calcium imaging, and behavioural measures (such as reaction time and decision choice) [9, 23, 8, 13, 4]. Questions of interest may include how to analyse spike trains from ensembles of hippocampal place cells to infer a person's position in the environment or how to identify the sources of dipole using multi-channel MEG recordings. Regardless of their specific modality and applications, SSM provides a unified and powerful paradigm to model and dynamically analyse these signals in both time and space.

## 2.1 State-Space Model Estimation Methods

One can estimate state-space models from MATLAB using one of the following estimation methods:

1. N4SID — this is a non-iterative, subspace method. The method works on both time-domain and frequency-domain data and is typically faster than the SSEST algorithm. One can choose the subspace algorithms such as CVA, SSARX, or MOESP using the n4Weight option. One can also use this method to get an initial model, and then refine the initial estimate using the iterative prediction-error method ssest [20, 19, 29, 16].

2. SSEST — this is an iterative method and uses a prediction error minimization algorithm. The method works on both time-domain and frequency-domain data. For black-box estimation, the method initializes the model parameters using n4sid and then it updates the parameters using an iterative search to minimize the prediction errors. One can use this method for structured estimation using an initial model with initial values of one or more parameters fixed in value [29, 21].

3. SSREGEST — this is a non-iterative method. The method works on discrete time-domain data and frequency-domain data. It first estimates a high-order regularized ARX or FIR model, converts it to a state-space model, and then performs a balanced reduction on it. This method provides improved accuracy on short, noisy datasets [19, 21].

With all the estimation methods, one has the option of specifying how to handle the initial state, delays, feed-through behaviour, and disturbance component of the model when applying behaviour metrics

# 3 METHOD

The data used for the analysis was a predefined dataset from an experimental setup [18, 17] on user perception to dynamic contents on webpages, it contains user attributes with the physiological response (Skin conductance response (SCR), Pupil changes, Skin Temperature (ST) and fixation location.

These user attributes are set using a multimodal measuring sensor that captures and synchronises the user response based on a predefined timestamp. The three state-space models were used as the inference engine for the data inputs, the main aim was to see which of these models best suits the dataset based on a prediction of the cognitive response of the user to the visual stimuli (webpages), the data contains average contents of user attributes such as other user activities like a mouse click, keypress and web addresses (URL). To analyse such a complex display of data, the use of dynamic control systems for physical processes is required, these state-space models are standard and engineered to build error-free prediction processes i.e. they are capable of error rejection, and great accuracy in performance even as an absolute negative prediction focus.

The model is adaptive to customised intelligent analytics (Figure 1) that can generate response data through signal processing and visualise the nature of the dataset through real-time simulation of its processes. The model is embedded with well-defined modules that hold the state-space models which were modified to suit the analytical processes. Response states are predicted for each control holding the modules and we can also analyse the prediction performance by autocorrelation and re-authentication of the entire process for system and data alteration. Given the customised nature of the data, the analytics is capable of applying a moving average filter that smoothens the response readings for baseline estimates to detect the tonic and phasic changes of the readings from the user's physiological response.

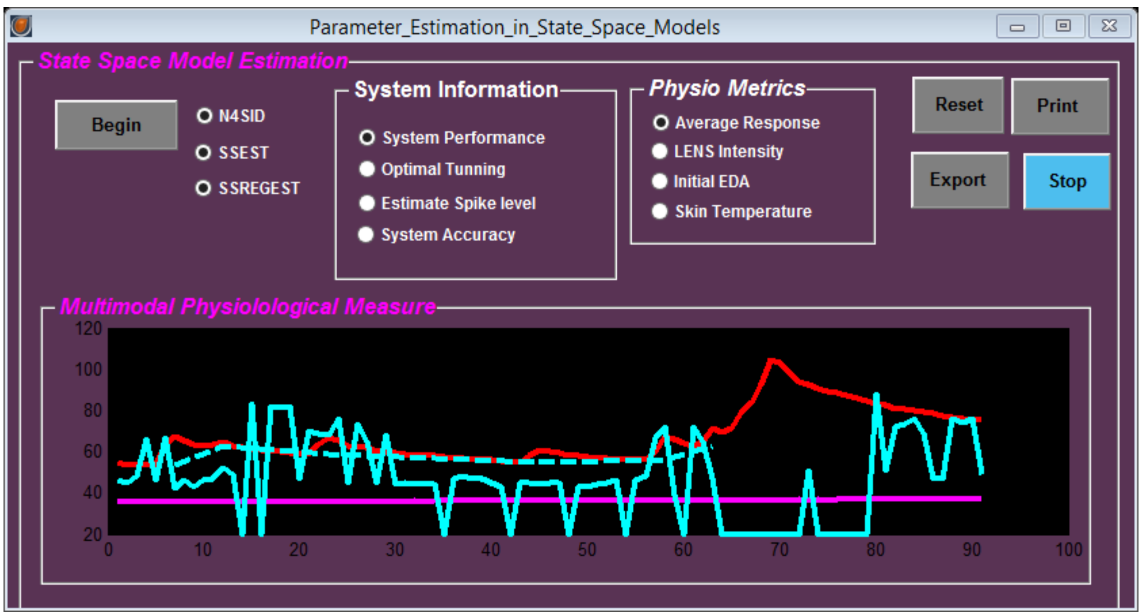



Figure 1: Index page of intelligent physiological response analytics with modules on integrated state-space controls

# 4 RESULT

The result from each resultant response of state-space models was analysed and Figure 2 shows the performance in system authentication, each attribute is significant and contributes to the accuracy and performance of the model. The reaction to stimuli is based on a third-order differential equation and this is simulated based on the input reaction at the initial stage of stimuli onset. The onset is based on a hand clap mechanism that sets the latency at a concise pre-set. The latency for each physiological response of the respondents varies because not all of them have the same skin tone and texture, some are found to be dehydrated and hence moisture content takes a while to be detected.

In a situation whereby no response reading is seen i.e. no peaks or spikes, the respondents are usually asked some questions in a subjective method to induce the process and reaction to the current situation. Environmental factors are sometimes considered and integrated into the study to make up for the lack of response and other noise in the dataset.

From Figure 2, the SCR seem to be the user attribute with the most contribution to error estimation, with an error rate of 0.06%. The SCR is most known to have a significant effect on response processes for all confined experiments involving the use of physiological response, it usually is known to correlate to users' emotional response to stimuli that would define their cognitive response and perception of the visual stimuli they interact with.

The ST is the hotness or coldness in response to stimuli and this is usually obtained from the temperature of moisture content, its contribution to system performance is an absolute $-0.09\%$ and an adaptive user attribute in this concept (physiological response), the Pupil changes is not only response the changes in light intensity but also an adaptive physiological measure to understand user cognitive state and emotion based on the dilation and constriction of the pupil in response to visual stimuli, this cognitive response can either be classified as stress or relaxed mood of the user. Its error rate lies at a minimum rate of 0.003%, which is far less than the other physiological responses and proves its assertion of having more access to the insight for understanding the cognitive response of a person. The fixation location ($MappedFY$) is simply the location the user looked at on the visual stimuli at a particular length of time, and it has an error rate of absolute $-0.00001\%$ as a contribution to the performance of the model. This accuracy is more feasible in detecting responses correlated to the visual stimuli.

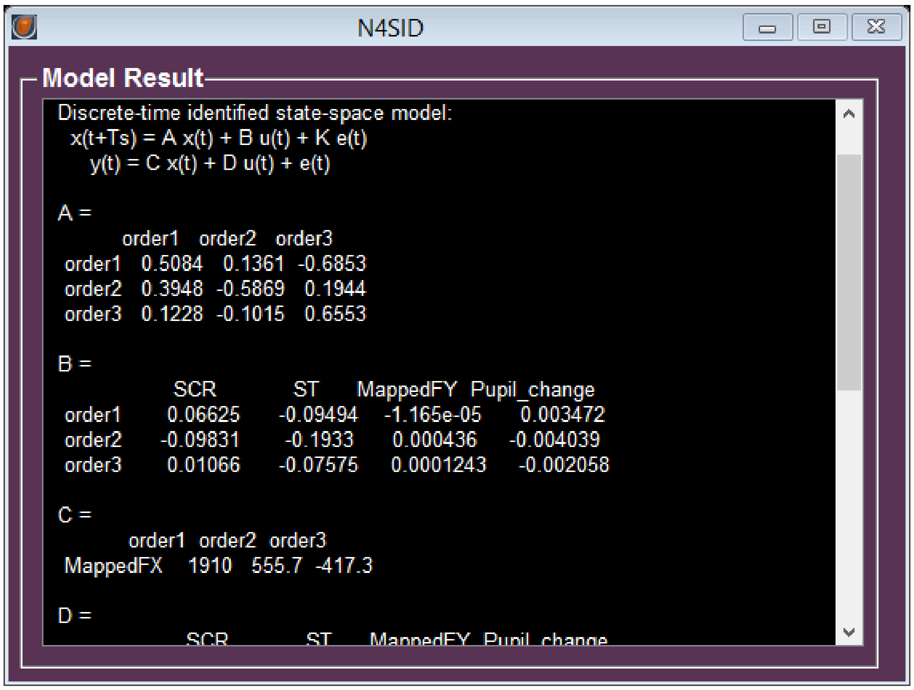



Figure 2: Result interface for N4SID modal with contributions of user attributes and performance of the model.

Figure 3 shows the user attributes of the response correlates, in this case, $x^1, x^2, x^3$, and $x^4$ represent the SCR, ST, $MappedFY$ and Pupil changes. Unlike the previous results, this model does not allow for custom attribute names but rather uses the default values, here SCR seem to be the user attribute with the most contribution to error estimation, with an error rate of 0.6%. The SCR is most known to have a significant effect on response processes for all confined experiments involving the use of physiological response, it usually is known to correlate to users' emotional response to stimuli that would define their cognitive response and perception of the visual stimuli they interact with. The ST is the hotness or coldness in response to stimuli and this is usually obtained for the temperature of moisture content, its contribution to system performance is an absolute $-6.35\%$ and an adaptive user attribute in this concept (physiological response), the Pupil changes is not the only response to the changes in light intensity but also an adaptive physiological measure to understand user cognitive state and emotion based on the dilation and constriction of the pupil in response to visual stimuli, this cognitive response can either be classified as stress or relaxed mood of the user. Its error rate lies at a minimum rate of 1.5%, which is far less than the other physiological responses and proves its assertion of having more access to the insight for understanding the cognitive response of a person. The fixation location ($MappedFY$) is simply the location the user looked at on the visual stimuli at a particular length of time, and it has an error rate of absolute $-0.7\%$ as a contribution to the performance of the model. This accuracy is more feasible in detection responses correlated to visual stimuli. Unlike the N4SID model SSEST, it is resistant to error, and not subservient to the performance of the model and hence its error rate is more than the previous state-space model.

Figure 4 shows the performance and error rate of the model and its user attribute contribution to the performance

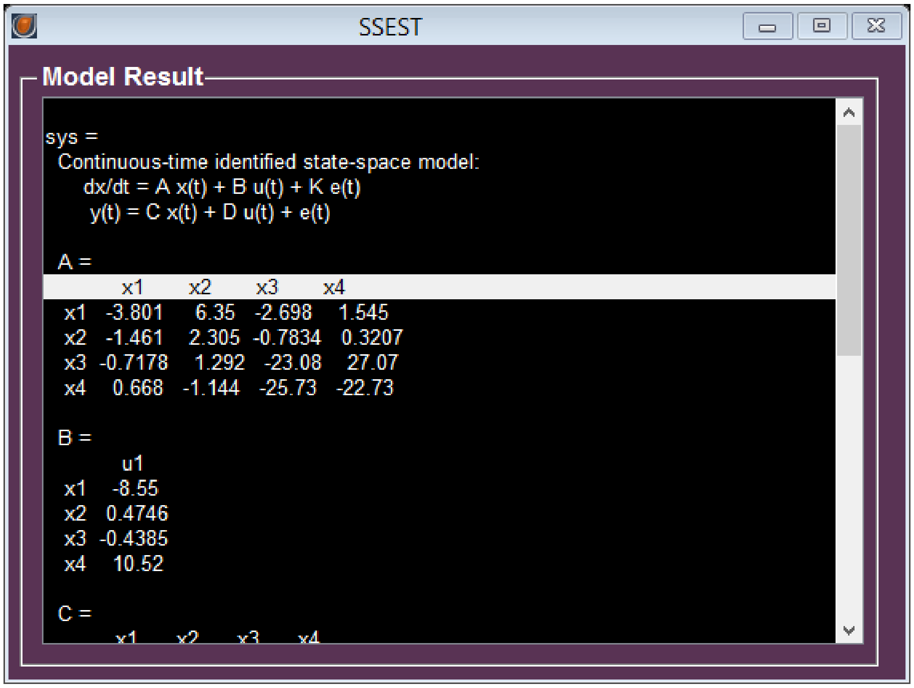



Figure 3: Result output for the SSEST model with response parameters state the error and accuracy of the attributes.

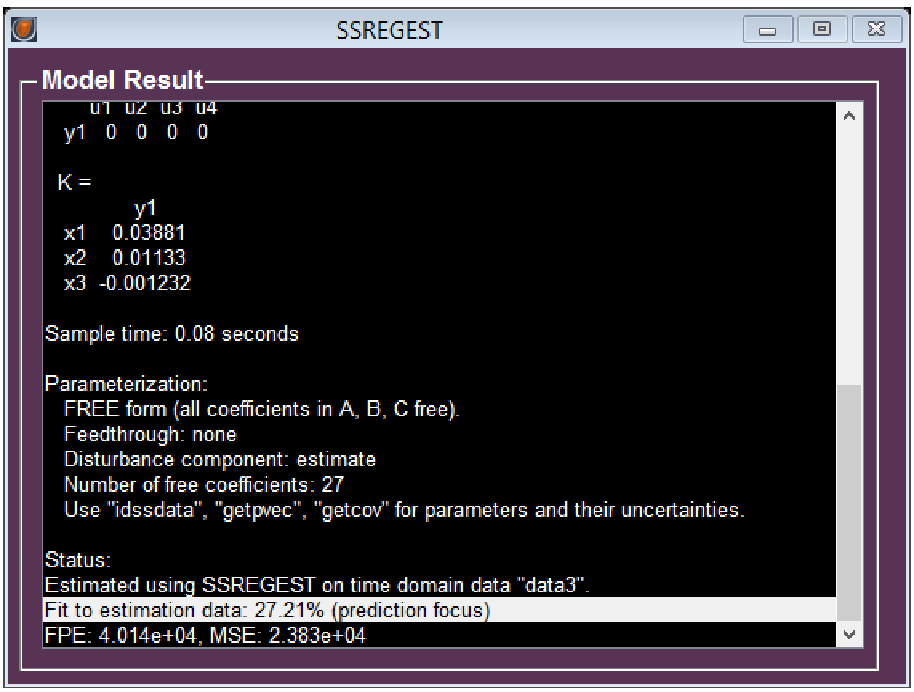
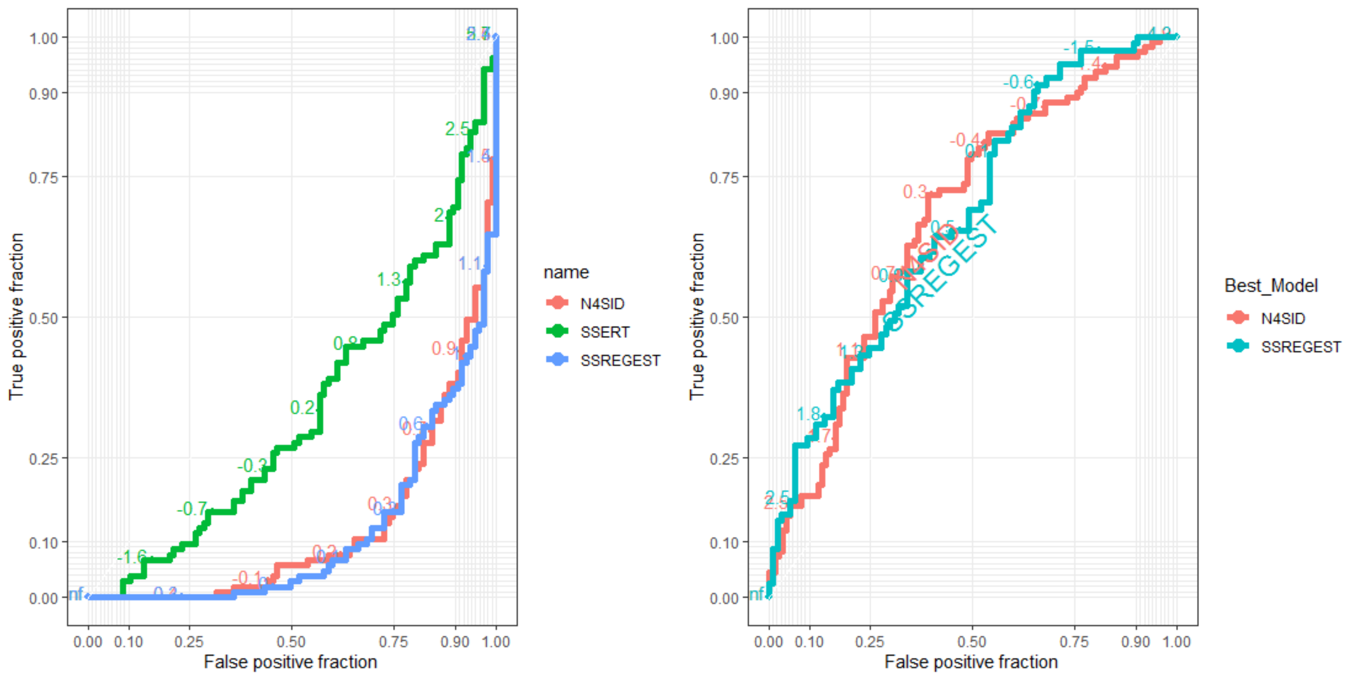



Figure 4: Window interface shows the performance of the SSRGEST model and user attribute contribution to the performance.

of the model. The parameters A, B, and C are free parameters that define this error rate. In this case, $u1, u2, u3$ and $u4$ represent the SCR, ST, $MappedFY$ and Pupil change, with a prediction focus of 27.21% and a means square error (MSE) of 0.0002%, the model is slightly resistance to error and the attributes contributes greatly to the model performance unlike the previous state space model (SSEST). The model is based on 0.08 secs and this minimum time interval is fast enough for a huge and complex dataset from the user perception and behavioural representation of the data. Figure 5a shows the aggregate of error in performance for all the state space models and N4SID has the least error with a minimum of 0.21%, this shows its reliability and accuracy in predicting user perception and behavioural attributes data which are usually very complex to predict. It also indicates its authenticity and applicability to the situation than the other state space models.




(a) Aggregate error in performance for all the state space models.

(b) Performance rate of the best two state-space models, with N4SID having the highest rate compared to SSREGEST.

Figure 5: Performance in Error and Highest level of models.

Performance on the best two models (N4SID and SSREGEST) was also investigated based on the plot in Figure 5a, to differentiate the performance ratings and authentication to its applicability. Figure 5b demonstrates that N4SID is highly resistant to error with a performance of 0.98% and can be compared to deep learning characteristical standards. The procedures in deep learning are already trained to mimic the human mind and brain processes and can perform far higher in behaviour predictions. Its applicability is well suited for situations like this, but order predictive models based on time series for physical systems are also very adaptive and can be modified for usability in areas like robotics to model the physical mechanisms and physiological processes. The methodology of physiological control systems can be modified to adopt standard procedures for physiological response prediction and detection that are adaptive to advanced techniques and modification stages of mechanical processes in physiological control systems.

# 5 CONCLUSION

This paper is aimed at demonstrating a dynamic comparison in time state-space models on identity psycho-physiological response data, it presents a novel measuring rate by applying three different state-space models (N4SID, SSEST, SSREGEST) in the prediction of physiological processes and a standard way of interpreting response potentials. The three different state-space models were used as the inference engine and the performance for each model is compared, the result shows that the four-order identified space model (N4SID) is most probable in interpreting physiological response with a performance of 0.98% focus. This would help in dealing with the choice of development of a physiological control system in the design of psycho-physiological mechanisms in a person or robotics. The future perspective is to integrate deep learning processes and compare the results obtained here to the performance that would be derived from deep learning, this would also contribute to the authenticity of the state space models.

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