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# Convergent Dynamics In Physiological Response As A Window-Based Robust Control System

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**Abstract**

*The process adapted here delivers physiological readings and maps out the major components that make up the physiological system. The contribution of this component can also be determined on each of the parameters. The skin conductance response (SCR) has a major effect on the synchronous readings of the physiological metrics used. The paper investigates this default by developing a prototypical representation of integrated physiological readings with real-time analytics using a convergent dynamic control model as the inference engine.*

*The major components that make up the physiological system and errors, are characterised by either their noisiness or systematic disturbance. The noisy error is based on the obvious pattern in each time interval and it is measured based on the mean root square error(MRSE). The SCR has a major effect on the synchronous readings of the physiological metrics used. The results obtained from test runs indicate that the Tonic phase of the physiological response signal is the skin conductance level (SCL) that represents the base level of the signal.*

*The Phasic level is the component of the skin conductance response that reflects the direct response to the external stimulus, and this is set between 1-4secs after the stimulus onset at the baseline phase. There also exists the non-specific SCR known as the anomalies that appear post-stimuli; this represents the number of conductance responses that appear within and among subsequent physiological response readings. The originality of work is its ability to visualise multi-modal response signals in a single frame and detect optimal responses significant to a particular event-related protocol.*

**Keywords:** Physiological control system, Engineering physiological system, Control parameters, Inference engine, Model optimisation

## Introduction

Very few studies have discussed the concept of the physiological system and its association with control dynamics and system engineering. Khoo (2018a), Manor et al. (2010), Stevens et al. (2018), Fetanat et al. (2019a), Das et al. (2011), Krendel and McRuer (1968) featured applications to the physiological response of non-linear dynamics, parameter estimation, and an adaptive estimation of the controls. The papers also illustrated key concepts and method that offers in-depth analysis of selected physiological control models that also highlights the topics in the paper presented. Appa and Argyris (1995), Babin (2021), Li and Liu (2012), Yang et al. (2014), Li and Todorov (2007), Lee and CHANG (1986), discusses the most noteworthy developments in system identification, non-linear dynamical analysis, optimal control and targets in current bio-engineering advancements. These are designed to be a form of practical resources with some text as guided experiments on simulated models.

The physiological control systems also focus on a common control and its principles that are used to characterize a broad variety of the physiological mechanism of the system. It explores both identical and non-linear and time-varying systems that provide the background for understanding the link between continuous-time and discrete-time dynamic models. This paper explores the inference dynamic control of the physiological system with a convergence higher-order dynamic system to a first-order system:

$$\ddot{x} = f(x,x,\dot{u}) \qquad (1)$$

Where *x*” is the input physiological metrics due to second-order changes in reaction to a stimulus $x$' is the first-order change while $u$ is the additional environmental constraint. This relates to state control acceleration of the state:

$$\ddot{x} = (d^2x)/(dt^2) \quad (2)$$

where the stacked change or resultant output in the state can be defined as:

$$y = \begin{bmatrix} \dot{x} \\ \dot{x} \end{bmatrix} \quad (3)$$

with a first-order form given as $y' = g(y,u)$. The research objective is set in such a way as to determine the resultant effect:
$y(t)$ for $t > 0$ subject to environmental constraint $u(t) = g((x),t)$ and latency
$x(0) = x_0$

Where $g((x),t) = d(x,u(x,t))$ is the time-varying dynamic function of the second-order differential equation. This process is modelled and simulated based on time interval $t$. The main purpose of the convergence dynamics is to determine how the response time and reaction act on the mechanism, the purpose of the control is to determine the system's possible response to errors and anomalies. Studies by Smet et al. (1990), Sarkar et al. (1994), Hu et al. (2003) and Koren (1985) have shown the positions of mechanical systems in robotics and how to generate continuous paths.

The main factor, is that executing these paths requires more conscious thought and more carefully designed physics for the mechanical systems and their mechanisms. The strongest response in a person can change instantaneously with time in the external environment. It is through the use of the control that mechanical systems like the robot move to a positive position with sub-millimetre accuracy, this is a means for understanding the locomotion and reflexes in the biological sensorimotor system.

These techniques can also be applied to human physiological response systems. Also, both dynamics and control have deep fields and can be studied in the present and in the future. However, there are significant changes in classical approaches which now rely heavily on mathematical models and analysis rather than computation as the key tool. Studies done by Monostori et al. (2016), Kim et al. (2012), Horv´ath et al. (2017), Lee et al. (2015), Franklin et al. (1998), have shown the basic concepts that change continuously over time in a physical system with $x \epsilon R^n$ being the defining quantity of the state of the system, the control input can be defined as $u \epsilon R^m$ , where $m$ is the number of independent chosen parameters or components. The six joint controls of the robot system are considered as $x = (q,v) \epsilon R^{12}$ and the control variables are set as $u = (v_{d1},...,v_{d0})$ where vdi indicates the desired flexibility of the response in the robot, and $i$ is the joints that make up the robot. These are a few examples of the application of dynamic control systems to biological processes. The main purpose of the control is to take charge of deviations from the idealised state process state and signal transmission besides handling the differential constraint of the convergence dynamic function. Some problems are foreseen during this period such as noise, bias, errors or uncertainty and disturbances. The robot reflex could fail to respond to a stimulus or reach an unrecoverable state of awareness. A robust controller can then be designed to produce high-quality behavioural deviations that recognise errors in a tightly controlled experimental condition.

## Literature Review

Recent studies by Kotas and Medzhitov (2015), Nanney (1958), Schweppe et al. (1980), Shadel and Horvath (2015), Pickles et al. (2018), covered the control mechanisms that provide the basis for the maintenance of homeostasis at every level of organisation in the hierarchy of living or biological systems (Figure 1). These are the working knowledge of the given biological system which is mostly incomplete unless we arrive at some understanding of the regulatory processes that mostly contribute to the natural operation of the characteristics of the body functions. Liem et al. (2013), Chen and Stroup (1993), Mel˜ao and Pidd (2000), Ellis and Wainer (1994), Peuquet (1994), maintain that to attain an understanding of the body functions the conceptual model of the different interacting processes is involved which is required and sufficient for response parameterisation. Uchino et al. (1996), Stemmler (2004) state that to determine whether or not one model reflects the underlying reality, one has to make the predictions with the model, the factors in play are often complex and dynamic and their behaviour may depend strongly on the numerical values of certain key parameters. In such a case, the rigorousness provides a quantitative approach to indispensable constraints. Some of the most notable advances in the physiological processes over the past decades such as that applied in Uchino et al. (1996), Stemmler (2004), Stevens et al. (2018), Darrall (1989) have been made through the application of quantitative models. The physiological control models also have been critical either in both direct and indirect conditions for the development of different improved medical diagnostic techniques and also novel technological therapeutic innovations in current times. The study of the physiological control system is generally incorporated as noted by Khoo (2018b), Fetanat et al. (2019b), Petrou et al. (2017), Enderle and Bronzino (2012), because of its importance and in one form or another into the study curriculum in schools under biomedical engineering. A lot of high-quality research by Doyle et al. (2013), Benner et al. (1999), has topics published over the years with a comprehensive text on the upper level of educational parastatals, such as the application of control theory to physiological systems with methods that employ convergence procedures.

The primary goals of most of the research areas by Bobtsov et al. (2011), Khoo (2018c), is to highlight the basics and techniques employed in the control theory, model identification, and system analysis and to give a precise biomedical engineering study to educational fields that would appreciate how the principles applied can be better understood in terms of the processes involved in physiological response and regulations. The assumptions made in some studies by Glass and Mackey (1979), Mackey and Glass (1977), Glass et al. (1988), Li (2015) on physiological control systems and analysis is the physiological applications of control engineering and its focus on the analysis of feedback regulation in contrast to the basic concepts and methods of the control theory to mathematics derivations and proofs. Points are also stated on the differences between technological and physiological control systems, and its introduction to the basic concepts of classical control theory of the physiological control systems. The study state analysis of the physiological closed loop systems which can be explored in a traditional term that relies on the graphical solution or in the form of a window-based dynamic control as in the case of this paper. This is a more modern approach that employs computer analytics to solve the problems of tonic, phasic and baseline estimates of physiological response systems in terms of error recurrence.

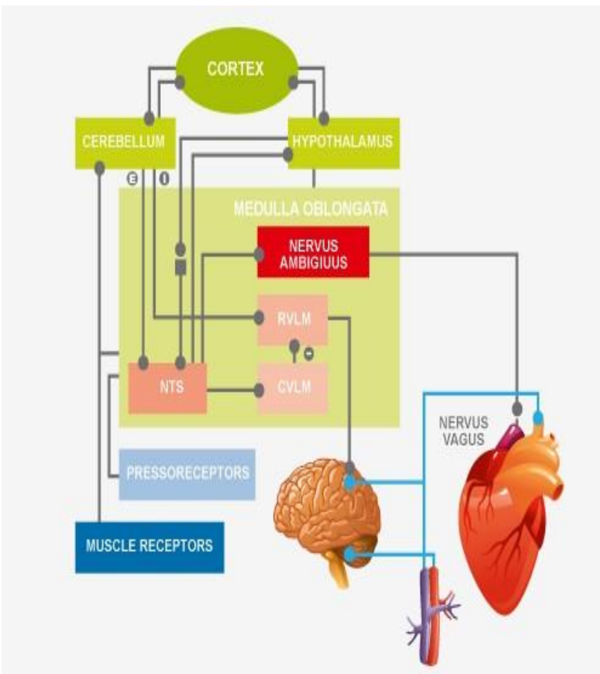



**Figure 1:** An integrated physiological system of the body: Courtesy: Google images.

Some studies Hunt et al. (1992), AlOmari et al. (2012) cover the topic of stability issue, which is of critical importance to the physiological regulation of the body, with a range of techniques for assessing stability under different conditions in the assumption of linearity of the physical system. Few studies like Ijaz et al. (2020), Murray-Smith (1982), Zamek-Gliszczynski et al. (2013) have paid particular interest in the physiological control issues related to parameter identification, sensitivity to noise and input in the design. Other works by Vancouver (2005), Duarte-Galvan et al. (2012), Jagacinski and Flach (2018) studied the application of modern methods such as the control theory to physiological systems. The methods are based on the principle of optimisation and the adaptive control theory applied to regulated spontaneous fluctuations in the physiological signal. Some more common non-linear analysis methods employ the investigation of the physiological system which recognizes space constraints to non-linear techniques and applications. This paper focuses mostly on the basic parameter components that make up physiological readings and one of its major contributions is the integration of the convergent dynamics to the multi-modal physiological readings (signals) and parameter estimates which can be applied in real-time. The proceeding sections discuss methods and results from the proposed model design (Figure 2 and 3).

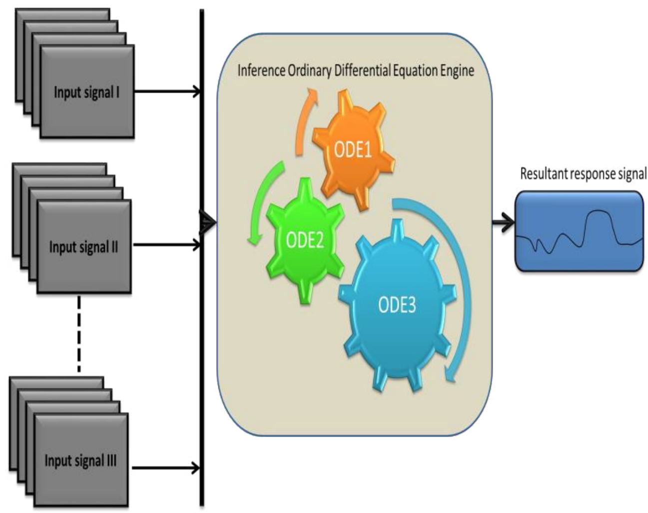



**Figure 2:** Response signal serve as input to inference ordinary differential equation engine.

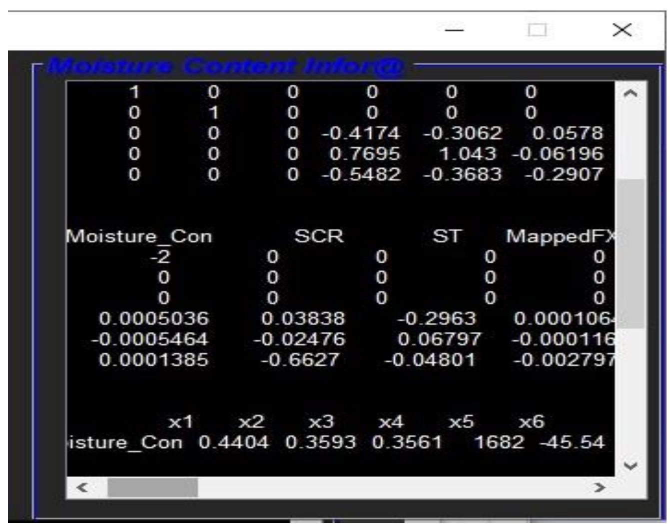



**Figure 3:** Physiological metrics with computer components.

The Skin conductance response is the major marker for detecting the cognitive state of a person and this is used here based on its measurement of moisture content related to sweat on the surface of the skin due to cognitive workload.

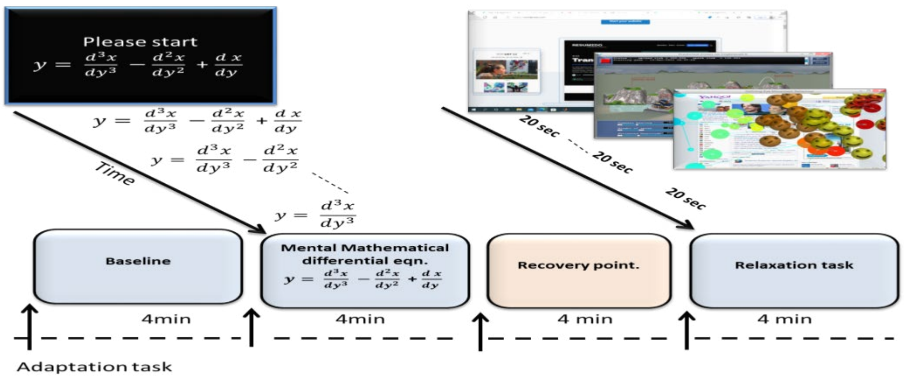



**Figure4:** Mathematical differential equation task allocation to participants.

## Methods

Errors are characterised by either their noisiness or systematic disturbance. The noisy error is based on the obvious pattern in each time interval and it is measured based on the mean root square error (MRSE). The error can be systematic in the fact that it does not obey a pattern. For control, these natural deviations usually fall under two types of fundamental groups, such as response uncertainty and emotional state uncertainty in a person. The disturbance is also a form of movement uncertainty that is caused by the state to which the movement is unexpected in a person such as distractions during an experimental study. Another form of this disturbance can be the nature of the room or room temperature which sometimes contributes to an increase in temperature in a normal body response. The major error that was tackled in the study is the measurement error, a state uncertainty that is due to the sensor's noise which is observed incorrectly. This is critical for a closed-loop controller in the measurement sensor and also the behaviour of the measure state. It can also be similar to modelling error or the parameter uncertainty that includes the convergent dynamic function, which differs from the human response. This is treated as state uncertainty in the response motion as is modelling as a disturbance to the convergent dynamics given as:

$$x^{\cdot} = f(x,u) + \epsilon_d \qquad (4)$$

The response signal *x'* is a set vector as input from a physiological response to a given set of tasks composed of an aggregate of responses from participants.

## The Task

The allocated attention task in the experimental study was set as a given mathematical differential equation which the participants have to solve for four (4) minimum intervals and a relaxation task in form of the static webpage was served to reduce their cognitive responses every twenty (20) seconds. The adaptation task is set in the form of a relaxation period where each participant is given orientation about the mathematical differential equation task on how to solve each given problem set in front of them. The skin conductance response and skin temperature were recorded, while the pupillary response was recorded from the eye tracker hosting the external stimulus. A total of sixteen (16 mins) was used to obtain the overall response signal. The participants (50 people) were selected from different parastatals regardless of gender and age differences. The rationale is to give a generalised viewpoint on response detection at the initial stage. They simply had to sign a consent form and agreement to take part in the study that uses a non-invasive biosensor SCR tool and a local webcam embedded in a labtop. The generated data is modelled in a convergent input setup in the form of a mathematical model.

Equation 9 is the given mathematical model that represents the input signal with the first derivative where $\epsilon_{d(t)} \epsilon E_d$ is the error. $E_d$ is the possible disturbance and probability function in the motor function. The state uncertainty can be modelled as the discrepancy between the estimated state *dy/dx* and the true state of the system x such that $dy/dx = x + \epsilon_x$. The modelled error is then treated as the state uncertainty on a different dynamical system on an augmented state transmission. Given a response controller with one-dimensional point mass, the unobservant true response *m* is due to the observed body response *m* which is usually due to response from the true value $\epsilon_m$ such that $m_b = m + \epsilon_m$. The augmented state vector $(p,v,m) \epsilon R^4$, results in the convergent dynamics:

$$\ddot{x} \equiv \begin{bmatrix} \dot{p} \\ \dot{v} \\ \dot{m} \end{bmatrix} = f(x,u) = \begin{bmatrix} v \\ f/m \\ 0 \end{bmatrix} \qquad (5)$$

Where the modelling error is equal to the state uncertainty response vector in the baseline response given as:

$$\epsilon_x = \begin{bmatrix} 0 \\ 0 \\ \widehat{m_1 - m_n} \end{bmatrix} \qquad (6)$$

The difference between the response time interval of the convergent dynamic system and the response trail is given as the response state space $x(t) : [0,T] \rightarrow R^n$ is the parametric response time interval. The physiological response reading can be visualised within a window-based dynamic control system with different parameter estimates (Figure 5). For this study the main physiological components treated include the Skin conductance response (SCR), Skin temperature (ST), Pupil response and their general baseline.

## Result

The Tonic phase of the physiological response signal is the skin conductance level (SCL) that represents the baseline level of the signal. The Phasic level is the component of the skin conductance response that reflects the direct response to the external stimulus and this is set between 1-4secs after the stimulus onset at baseline phase (Figure 6).

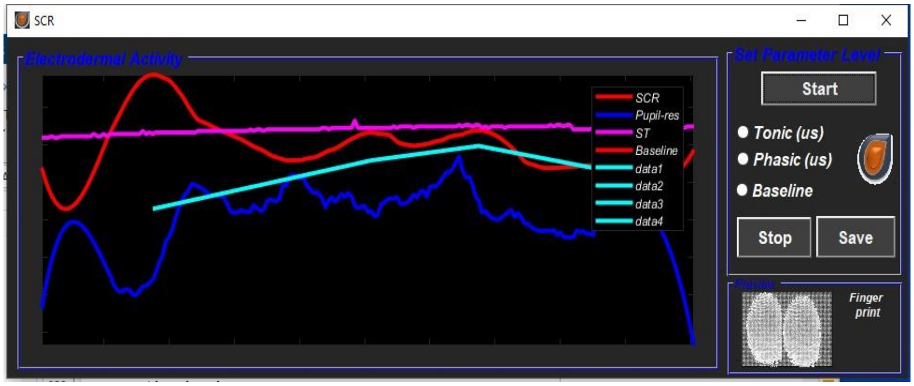



**Figure 5:** Index page of the Convergent dynamic control model

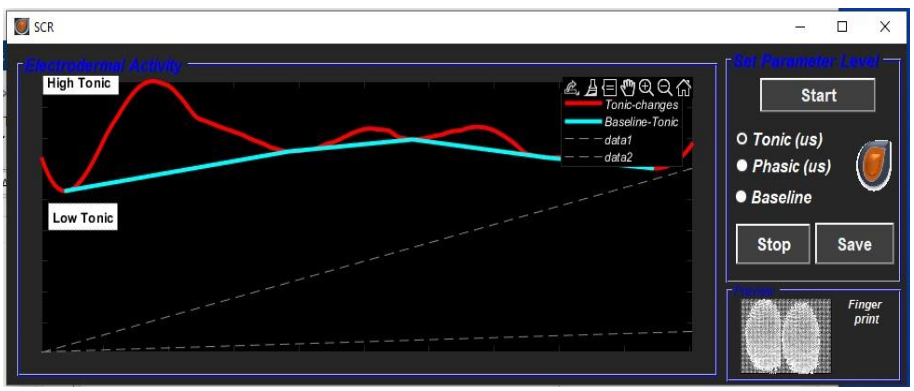



**Figure 6:** The changes in Tonic phase on both skin conductance (low tonic) and skin conductance level (high tonic).

There also exists the non-specific SCR known as the anomalies that appear post-stimuli; this represents the number of conductance responses that appears within a period. In this case, the parameters feature extract components from the SCR and anomalies interval at an adaptation time interval. This is calculated based on 20secs overlapping time window frames for both stimulus onset and every recovery time interval respectively. The parameters of the tonic phase were computed based on every last 20-sec interval; for the relaxation task, the first 20-sec period was selected to reflect a response to the stimulus, while for the mathematical differential equation task, the final 20-sec periods of each of the phase was used to determine the response to amplitude for the task for every participant. The aggregate response is used to represent the overall response to external stimuli.

Figure 6 shows the window frame for the overall physiological response. The SCR (red line) is decomposed to Baseline (Cyan color) and represents the slow-varying optimal tonic phase of the skin conductance. The amplitude of the SCL is the standard derivative of the Skin conductance response and the slope of the SCL.

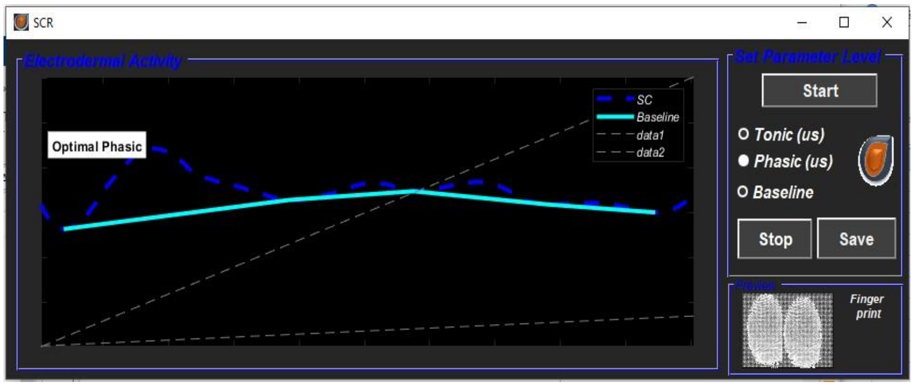
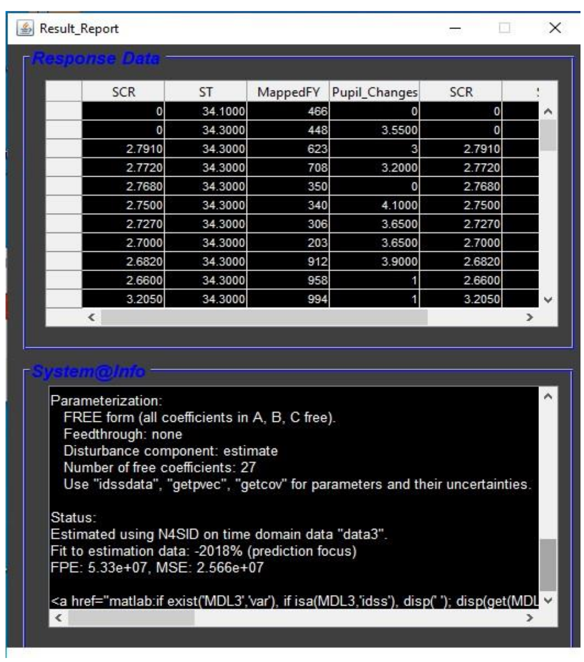



**Figure 7:** The baseline of the skin conductance to the maximum SCL or optimal phasic level at the peak of the response.

The dashed blue line of Figure 7 shows the baseline of the skin conductance to the maximum SCL or optimal phasic level at the peak of the response. Sometimes external causation due to experimental setup called artefacts in the data can affect SCL baseline, and the minimum baseline is estimated before the peak (minimum SCL) which is used as a baseline measurement for all physiological responses. The latency is the time delay from the onset to the start of the SCR; this is the SCR that crosses the 0.03µs detected at the set threshold and is a typical representation of a 1-3 secs response interval. The rise time denotes the time from the SCR at the onset to the peak response (maximum SCL). The time to an increase in amplitude is the same as the latency and rise time. The sampling window is based on latency taken from the conductance response presented at the time of maximum baseline or optimal phasic change. The baseline response is obtained by using the Savistky Golay filter to smoothen the original SCR and this is done for each physiological response such as the skin temperature, pupil response and baseline response. The Tonic skin conductance is the average response from the SCR; these are measured as lower trace mark (Cyan color) as the Phasic level and used to determine when a set threshold of $0.03\mu s$ is passed for every event-related response identified in the automated dynamic control analysis. The push-menu buttons can be automatically activated to display the real-time analysis of the signal response of each parameter computed using the convergent dynamic control model.

Each physiological metric indicates a contribution to the performance of the dynamic control shown in Figure 9. Each of the data metric reliability is based on the error test computed from the window frame of (Figure 8), the standard error for each input signal for the model attributes is given as 2.10%, this exceeds the standard threshold for a typical physiological response signal. It can also the termed as feasible since behaviour data is usually difficult to predict. The application of standard biomedical tools has also contributed to the decrease in false positive cases in response detection.




| SCR | ST | MappedFY | Pupil_Changes | SCR |
|---|---|---|---|---|
| 0 | 34.1000 | 466 | 0 | 0 |
| 0 | 34.3000 | 448 | 3.5500 | 0 |
| 2.7910 | 34.3000 | 623 | 3 | 2.7910 |
| 2.7720 | 34.3000 | 708 | 3.2000 | 2.7720 |
| 2.7680 | 34.3000 | 350 | 0 | 2.7680 |
| 2.7500 | 34.3000 | 340 | 4.1000 | 2.7500 |
| 2.7270 | 34.3000 | 306 | 3.6500 | 2.7270 |
| 2.7000 | 34.3000 | 203 | 3.6500 | 2.7000 |
| 2.6820 | 34.3000 | 912 | 3.9000 | 2.6820 |
| 2.6600 | 34.3000 | 958 | 1 | 2.6600 |
| 3.2050 | 34.3000 | 994 | 1 | 3.2050 |

**Figure 8:** Convergent dynamic transform of the model.

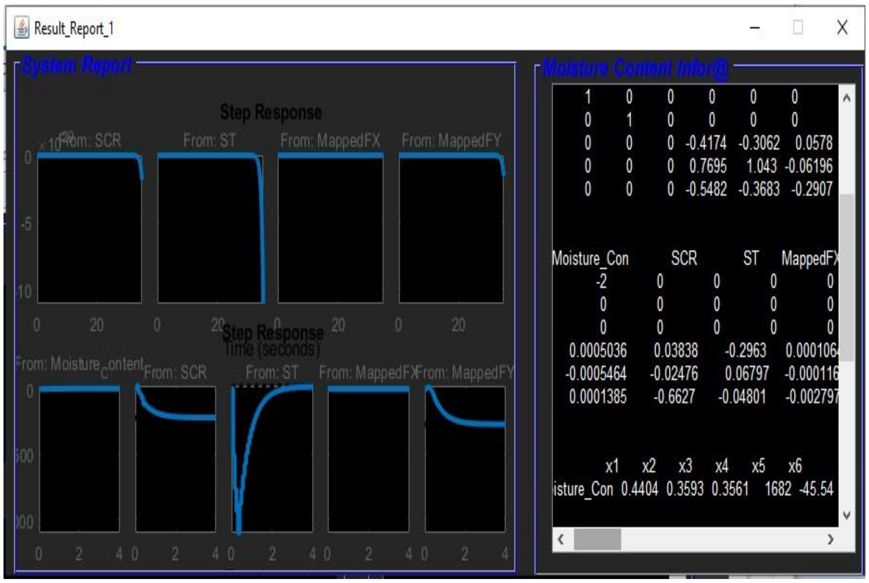



**Figure 9:** Performance metrics for each physiological response served as input to the convergent dynamic control.

## Conclusion

This paper seeks to investigate the trends in convergent dynamics in physiological response modelling in the form of a window-based robust control system. The concept of physiological phenomena and engineering control systems can be termed as being similar to each other in the sense that the physiological control explores the biological environment that also includes a person by providing a solution to the control, while the engineering control explores the software and hardware of a physical system. The biomedical application is more efficient and natural due to the involvement of control theory; the mechanism of the control system comprises components which are necessary for both maintenance and homeostasis in the living systems of a person. The negative and positive feedback control its mechanisms is used for maintaining its homeostasis. The major default is the ability to visualise its process in a single frame for easy and real-time model optimisation. The paper investigates this default by developing a prototypical representation of integrated physiological readings with real-time analytics using a convergent dynamic control model as the inference engine. The process delivers physiological readings and maps out the major components that make up the physiological system. The contribution of this component can also be determined on each of the parameters. The SCR has a major effect on the synchronous readings of the physiological metrics used. The future work would be to embed real-time analytics for online response detection with a multi-modal measuring biosensor both in mobile and desktop operating systems that would integrate real-time analytics to response detection. This would also include the pupil detection sensor that synchronises the effect of the external stimulus to other sensors used within a single frame.

## Abbreviations

1. Mean Root Square Error (MRSE).
2. Skin Conductance Level (SCL)
3. Skin Conductance Response (SCR)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