Theoretical Basis of Human Sensory and Motor Processing in Simple Reaction Time Tasks

by

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Institute of Biomaterials and Biomedical Engineering
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Abstract

Simple reaction time (SRT) is the minimum time taken to make a motor response given a sensory stimulus. Studies on SRT help uncover pathways by which sensory and motor processing take place. A theoretical framework based on the entropy of the stimulus has been used to derive an equation governing SRT. This thesis explores the efficacy of this SRT model. The derived equation generates accurate predictions not only for reaction time, but also for threshold experiments governing the tradeoff between stimulus duration and intensity. The results from both experiments can be described by equations derived from the entropy model using the same set of parameters. The results of this study not only provide a promising method for studying sensorimotor integration, it also demonstrates the ability of the entropy model to unify both sensory and motor processes.
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Acknowledgments......................................................................................................................iii
Table of Contents............................................................................................................................iv
List of Tables.....................................................................................................................................vii
List of Figures.....................................................................................................................................viii
List of Appendices.............................................................................................................................x
1. Introduction....................................................................................................................................1
2. Background....................................................................................................................................3
   2.1 The study of psychophysics.......................................................................................................3
      2.1.1 Intensity discrimination....................................................................................................3
      2.1.2 Magnitude estimation.......................................................................................................4
      2.1.3 Threshold detection..........................................................................................................5
      2.1.4 Simple reaction time.........................................................................................................5
   2.2 The entropy theory...................................................................................................................8
      2.2.1 Relationship between the entropy model and other psychophysical laws.................9
      2.2.2 Model comparison to real data.......................................................................................10
   2.3 Motor physiology....................................................................................................................13
   2.4 Sensory-motor integration......................................................................................................14
3. An entropic Simple Reaction Time (SRT) model.........................................................................16
   3.1 Derivation of the SRT model from the entropy of the signal..............................................16
      3.1.1 Model performance on real SRT data.............................................................................18
      3.1.2 Comparison between the entropy SRT model and Piéron’s law.................................21
   3.2 Adding a constant motor delay.............................................................................................22
3.2.1 SRT vs. body size........................................................................................................24
3.3 Re-interpreting the SRT model..........................................................................................26
4. Separating the sensory and motor components of SRT.....................................................32
  4.1 Motivation for the experimental study.............................................................................32
   4.1.1 Absolute Threshold (AT) vs Simple Reaction Time (SRT)........................................32
   4.1.2 Deriving the AT model from the entropy model.........................................................33
  4.2 Methods..........................................................................................................................35
   4.2.1 Participants................................................................................................................35
   4.2.2 Sound level calibration..............................................................................................35
   4.2.3 AT experiment............................................................................................................37
   4.2.4 SRT experiment ........................................................................................................38
  4.3 Results............................................................................................................................40
   4.3.1 Measurements from AT & SRT experiments...............................................................40
   4.3.2 Curve fittings using the entropy model....................................................................43
5. Summary, discussion and conclusion..............................................................................49
  5.1 Thesis summary..............................................................................................................49
  5.2 Discussion.......................................................................................................................51
   5.2.1 Entropy theory & estimated parameters.................................................................51
   5.2.2 Sensory & motor components – serial or parallel?..................................................52
  5.3 Other literature...............................................................................................................53
   5.3.1 Sensory & motor components of SRT.......................................................................53
  5.4 Future work and conclusion..........................................................................................55
Bibliography.........................................................................................................................57
Appendices ..............................................................................................................................67
A.1 Derivation of the entropy model .................................................................67
A.2 Testing system delay of SRT experiments ...................................................71
List of Tables

Table 3.1 – Values of all SRT model parameters estimated using data obtained from experiments on audition and vision (Chochole, 1940; Jaśkowski et al., 1994; Doma & Hallett, 1988; Gilden et al., 1966) ................................................................. 20

Table 3.2 – Ranges of parameter “n” and “t_{rmin}” for audition and vision SRT experiments ...... 20

Table 3.3 – Values of new model parameters estimated using the same data as Table 3.1 (Chochole, 1940; Jaśkowski et al., 1994; Doma & Hallett, 1988; Gilden et al., 1966) ................. 24

Table 3.4 – Comparison between body heights and the estimated values of t_{rmin} ............... 25

Table 4.1 – Values of all SRT model parameters estimated from curve fittings using the entropic SRT equation .................................................................................................................................................. 45

Table 4.2 – Values of t_{rmin} / n and a obtained from simultaneous curve fittings using entropic AT & SRT equation .................................................................................................................................................. 48
List of Figures

Figure 2.1 a) – The entropy model’s prediction on the pattern of weight perception. The original data was obtained from an experiment conducted by Luce and Mo (Luce & Mo, 1965).............11

Figure 2.1 b) – The entropy model’s prediction on sweetness perception of sucrose. The data was obtained from an experiment conducted by Moskowitz (Moskowitz, 1970)...............................11

Figure 2.2 a) – Fitting of Eq. (2.6) to the adaptation pattern of hunting spider mechanoeceptor (Bohnenberger, 1981); ‘d’ represents the stimulating amplitude (I’ = 0.395, 0.0975).........................12

Figure 2.2 b) – Fitting of Eq. (2.6) to the neural adaptation pattern of sugar receptor of blowflies (Dethier & Bowdan, 1984); each curve represents the measurements taken with different sugar concentrations (I’ = 1, 0.1, 0.01).................................................................................................13

Figure 3.1 – Curve fits of auditory and visual SRT measurements using Eq. (3.10) (Chocholek, 1940; Jaśkowski et al., 1994; Doma & Hallett, 1988; Gilden et al., 1966).................................19

Figure 3.2 – Curve fits of auditory and visual SRT measurements using Eq. (3.14) (Chocholek, 1940; Jaśkowski et al., 1994; Doma & Hallett, 1988; Gilden et al., 1966).................................23

Figure 3.3 - Curve fit of motoneuron firing rate adaptation using the entropy adaptation model (Eq. (2.6)) (Desmedt & Godaux, 1978)........................................................................................................27

Figure 3.4 - Curve fit of frog muscle end-plate current using the entropy adaptation model (Eq. (2.6)) (Magleby & Stevens, 1972)........................................................................................................28

Figure 3.5 - Curve fit of the relationship between force output vs. motoneuron excitation rate using the entropy model for magnitude estimation (Eq. (2.2)) (Petitjean & Bellemare, 1994).....28

Figure 4.1 – Diagram of the experimental system.................................................................39
Figure 4.2 – Comparison between the data obtained from the AT experiment and SRT experiments for all participants.................................................................41

Figure 4.3 – The difference between the averaged data obtained from AT experiment and SRT experiments..................................................................................................................42

Figure 4.4 – Curve fitting results of SRT #2 data using the entropic SRT equation.................44

Figure 4.5 – Simultaneous curve fitting results of the AT and SRT experiment #2 data using the entropic AT & SRT equations........................................................................................................47

Figure 5.1 – Rough sketches showing qualitative results of the experiments..........................50
List of Appendices

A.1 Derivation of the entropy model.................................................................67

A.2 Testing system delay of SRT experiments..................................................71
1. Introduction

Reaction time is defined as the time taken to respond to a stimulus. By studying reaction times, it is possible to uncover the pathways by which sensory, cognitive and motor processing take place. One of the simplest methods to measure reaction time is known as the Simple Reaction Time (SRT) task. It is defined as the minimum amount of time required for a subject to make a motor response to a stimulus. Studies on SRT have provided insights on how sensory information is processed, as well as how a response is generated by the motor system. Such knowledge can lead to better understanding of deficits in perception or motor response under various medical conditions (Simmons et al., 2010; Sylvain-Roy et al., 2010; Levin et al., 2011; Barr et al., 2014; Min & Min, 2014; Yalachkov et al., 2010). It can also be used to improve athletic performance or design better human action/reaction based systems (Dube et al., 2015; Cheng et al., 2008; Philip et al., 1999).

It has been known for more than a century that SRT decreases as the stimulus intensity increases (Cattell, 1886). Since then, various mathematical models of SRT have been constructed to study this relationship. The most well-known model was proposed by French psychologist Henri Piéron in the early twentieth century (Piéron, 1913; Piéron, 1952). It states that $t_r = CI^n + t_{min}$. $I$ represents the intensity of the stimulus. Both $C$ and $n$ are constants. $t_{min}$ stands for the minimum reaction time possible and $t_r$ is the predicted reaction time.

This kind of model is known as an empirical model. It refers to a situation in which the mathematical relationship is derived purely from the best fitting equation. In addition, theoretical models have also been created based on the physical or physiological nature of the phenomenon. In the context of reaction time, sensory perception and motor generation are often modeled as two separate processes.

In this thesis work, we would like to explore a previously derived model for SRT using the theoretical approach. A sensory model known as the entropy model was originally established by Kenneth H. Norwich (Norwich, 1977) in the 1970s. This SRT model was then obtained from
extending the entropy model to the motor domain. The goal of this research is to not only validate the efficacy of this SRT model, but to also demonstrate that the entropy model can predict both the sensory perception and the simple reaction tasks with the same set of model parameters. By doing so, it potentially “unifies” the sensory and motor processes and can reveal insights on the fundamental basis of information processing through both pathways.

In section 2, we will start with a general overview of the famous models that were previously developed for various sensory and motor phenomena. We will then introduce the entropy model that the SRT model is based on. The efficacy of the entropy model will be demonstrated by comparing its predictions of various sensory phenomena to real data. And finally, to evaluate the SRT model for reaction task prediction, some background physiology of the motor system will be discussed.

Section 3 will begin with the derivation of the SRT model from the entropy model. The effectiveness of this SRT model will be evaluated via curve fittings and analysis of model parameters. Based on the result of the analysis, we will show that the original attempt to extend the entropy model from the sensory to the motor domain could not yield satisfying results. To resolve this, several additional attempts were made to complete the derived SRT model using motor physiology.

Section 4 is the main part of the thesis. Here, we chose to explore the sensory and motor components of SRT experimentally. This can be done by comparing the results from threshold detection and simple reaction time experiments. We will also attempt to establish the theoretical connection between the two experiments by showing that the entropy model essentially “unifies” both processes.

Finally, section 5 will conclude the thesis work by giving an overview of everything done. There will also be a comprehensive discussion on the results and implications of our experimental study as well as the significance of this research and potential future studies.
2. Background

Before examining SRT related studies, let us first focus on some major discoveries made in the field of psychophysics, as a large part of this thesis is based on much of the good work done in this field.

2.1 The study of psychophysics

Psychophysics is defined as the study of the quantitative relationship between a physical stimulus and the response it generates. Psychophysical studies often look for patterns in simple tasks like intensity discrimination, magnitude estimation, threshold detection and simple reaction time, in order to study the underlying mechanism of sensory and motor processes.

2.1.1 Intensity discrimination

In an intensity discrimination experiment, two stimuli with different intensities are presented one after another in a random order. The subject is asked to identify the stronger stimulus of the two. It turns out that the difference in intensities must reach a certain threshold value in order to provoke a consistently correct discrimination response. This differential threshold value is commonly known as the Just Noticeable Difference (JND).

One of the first psychophysics laws examined the pattern between these JNDs and the corresponding stimulus intensity. It was established by German physiologist Ernst Heinrich Weber and it stated that the ratio between the JND ($\Delta I$) to the stimulus intensity ($I$) remains constant (Drever, 1952):

$$\frac{\Delta I}{I} = constant.$$

The constant $\frac{\Delta I}{I}$ is also known as Weber’s fraction and this law is generally referred to as the Weber’s Law.
2.1.2 Magnitude estimation

German physicist Gustav Theodor Fechner built upon this relationship and established *Fechner’s law*. This law states that sensation increases as the logarithm of the stimulus (Fechner, 1860):

\[ S = A \log(I) + K, \]

where \( S \) is the subjective magnitude of sensation evoked by the stimulus. \( I \) is the stimulus intensity. \( A \) and \( K \) are both constants.

Fechner’s law was one of the first successful models to quantify sensation. It was widely used in the evaluation of stimulus intensity based on the subjective feeling they induced.

In the twentieth century, another empirical form of this relationship was proposed and quickly accepted by the psychophysical community. The famous *Stevens’ power law* proposed by Stanley Smith Stevens states that a power relationship exists between the stimulus intensity and the sensation it creates (Stevens, 1961):

\[ S = K I^A \]

Again, \( I \) is the intensity of the stimulus, \( S \) is the subjective magnitude of the sensation, \( A \) is an exponent that depends on the type of stimulus and \( K \) is just a proportionality constant that depends on the units used.

Various other expressions have also been put forward to describe this relationship, although Fechner’s law and Stevens’ power law are the most common.

The exponent parameter (\( A \)) in Stevens’ power law is widely believed to be related to the sensory modality (Teghtsoonian, 1971). An observed contextual effect called *range effect* also states that the exponent (\( A \)) is expected to be smaller with larger range of stimulus intensity (Engen & Levy, 1958; Künnapas, 1960; Bonnet, 1969; Teghtsoonian, 1971, 1973).
2.1.3 Threshold detection

Unlike the differential threshold mentioned in 2.1.1, an absolute sensory threshold refers to the minimum intensity required for stimulus perception. A threshold detection experiment uses methodology similar to the intensity discrimination experiment, with one of the two stimuli presented being absent. The subject has to indicate which stimulus is not absent. Measurements of this threshold help us decode the underlying mechanism of sensory processing.

In 1885, Bloch and Charpentier stated their law governing the threshold quantity of light energy required for perception. The law states that the minimum perceptible light intensity \(I_{\text{thresh}}\) is the function of the light duration \(t\):

\[
I_{\text{thresh}} \times t = \text{constant}
\]

In 1912, Blondel and Rey pointed out that with larger values of \(t\), the Bloch-Charpentier law can be generalized to the Blondel-Rey law:

\[
\frac{I_{\text{thresh}}}{I_\infty} = 1 + \frac{a}{t}
\]

\(I_\infty\) is the absolute minimum intensity for the light to be perceived (when the duration of stimulus is indefinitely long). \(a\) is known as the Blondel-Rey constant.

Hughes also found the same relationship for auditory threshold detection results (Hughes, 1946).

2.1.4 Simple reaction time

In 2.1.3, we looked at the relationship between the stimulus intensity \(I\) and duration \(t\). In this section, we explore simple reaction time (SRT), another relationship between stimulus intensity \(I\) and time \(t\).
2.1.4.1 An experimental view of SRT

Most SRT studies were conducted using reaction stimuli that ramp on rapidly and maintain the peak intensity for a fixed amount of time or until the subject has responded. In certain SRT experiments, subjects may find it difficult to maintain high level of attention at all times; warning signals are introduced as a result. These warning signals are typically in a modality different from the reaction stimulus. The time it takes from the end of warning signal to the onset of stimulus is called the foreperiod. Depending on the experimental design, foreperiods can be fixed or random. When constant foreperiods are used, catch trials with silent stimuli are inserted to prevent the subject from timing the reaction onset using the warning signal. Results obtained from the catch trials can be used to correct the potential bias in the experimental data. Considerable investigation has been made on this matter, but we will not provide more details now.

2.1.4.2 Piéron’s law

It has long been known that the mean human SRT decreases as the stimulus intensity increases. The SRT eventually reaches an asymptotic value \( t_0 \) for very intense stimuli in all sensory modalities. Piéron’s Law is likely the most well-known empirical law for SRT prediction (Piéron, 1952):

\[
(RT - t_0) = \beta I^{-\alpha}
\]

\( I \) is the stimulus intensity. Both \( \beta \) and \( \alpha \) are parameters. The \( t_0 \) is the fastest possible SRT measured using stimuli with indefinitely large intensities. And the \( RT \) is the measured reaction time.

Piéron’s Law was formulated as a simple effect of light luminance on reaction time. However, over the last century, the law has been reported in many different domains. These domains include tone detection (Chocholle, 1940), taste detection (Bonnet et al., 1999), odor detection (Overbosch et al., 1989), heat detection (Banks, 1973) and motion detection (Burr et al., 1998).
Similar to the exponent of Stevens’ power law, the value of exponent $\alpha$ has also been shown to depend on the sensory modality (Norwich, 1987, Pins & Bonnet, 1997, O’Donell et al., 2010). Furthermore, with similar experimental setup, the value of $t_0$ also varies with the type of stimulus. For example, it is well established that auditory and visual SRT ($t_0 \approx 100$-200 ms) in general is faster than taste SRT ($t_0 > 400$ ms).

2.1.4.3 Other SRT models

A wide variety of modern SRT theories was also proposed in order to decompose the detection-and-response-processing system.

One popular opinion is to treat the entire system as a serial processing pathway with different physiological stages. In 1860, Donders suggested that if we can find two tasks such that a particular information processing stage is present in one and missing in the other, the difference between their time taken is the duration of that stage (Donders, 1860). Inspired by this, both Sternberg and McClelland chose to decompose the simple reaction task into successive temporal stages called subprocesses (Sternberg, 1969; McClelland, 1979). Their SRT models are based on the assumption that information is transferred from one subprocess to the next in a unidirectional fashion.

Conversely, the famous race model claims that the SRT is the winning result of a race between the parallel processing of two stimuli. This model was first proposed by Raab to account for SRT measurements with two stimuli of different modalities presented at the same time (Raab, 1962). In 2003, Miller and Ulrich established a more general race-like SRT model called the parallel grains model (Miller & Ulrich, 2003). It assumes that the decision process is considered to be a race between these parallel sensory inputs to the motor system and the SRT is, therefore, determined by the fastest or the fastest groups of racers.

Burbeck and Luce also established an SRT model in 1982 (Burbeck & Luce, 1982). The model is formed based on a change-detector and a level-detector that function in parallel during stimulus
perception. The change-detector is sensitive to abrupt changes in stimulus intensity whereas the level-detector can respond to the changed stimulus long after the change is completed. The assumption is that two detectors function independently; stimulus detection is initiated by whichever responds first to the stimulus.

2.1.4.4 Choice reaction time

Choice Reaction Time (CRT) tasks are similar to SRT tasks, except that subjects may have to make choices from many possible stimuli or responses. An established fact about CRT is that, under the same experimental conditions, they could be 100-150 ms slower than SRTs. The data measured from CRT tasks are also usually more variable (Laming, 1968; Snodgrass et al., 1967). Many believe that most of this additional time is used for information processing required to distinguish among the possible stimuli, whereas others argue that such time is required to make a selection among the possible responses (Sternberg, 1969). The effect of intensity on CRT is also not as simple as it is on SRT. It was shown that the average CRT is a U-shaped function of intensity as opposed to systematically decreasing with higher intensity levels (Keuss, 1972; Keuss & Orlebeke, 1977). Moreover, in the context of SRT, the intensity was believed to simply affect the rate at which information about the stimulus accumulates. However, during a choice reaction task, the primary effect of intensity is suspected to be in the response selection stage of the process (Luce, 1986).

Although CRT can be very important for reaction time studies, in this thesis, we will only be focusing on measurements related to SRT experiments.

2.2 The entropy theory

A mathematical model was previously established by Norwich to describe various sensory phenomena (Norwich, 1977; Norwich, 1991; Norwich, 1993). It is derived based on information theory and the statistical properties of the sensory stimulus fluctuation pattern. One of its fundamental assumptions is that there is always an uncertainty or entropy level associated with
the sensory receptor during the process of perception. In the beginning of perception, the receptor’s uncertainty or entropy level is very high. As the receptor continues to sample the given stimulus, the entropy level drops while the information associated with the stimulus increases. Stimulus can only be detected when a critical amount of information has been collected. This is the entropy conjecture; we will, therefore, refer to the model as the entropy model for this thesis.

The entropy model states:

\[
F = k \times H = k \times \frac{1}{2} \ln(1 + \beta \frac{I^n}{t})
\]  
(2.1)

(See Appendix A.1 for the full version of model derivation)

\(H\) represents the entropy level of the receptor as mentioned above. \(I\) is the intensity of the stimulus, \(t\) is the duration of the stimulus. \(k, \beta\) and \(n\) are all model parameters. Parameter \(n\) was shown to depend on the sensory modality. \(F\) can denote both the neural firing pattern (imps/s) and the subjective magnitude of sensation and thus the unit of \(k\) changes correspondingly.

Unlike an empirical model fashioned from experimental results, the entropy model is derived theoretically using the entropy conjecture stated above. With one unique set of fundamental postulates on sensory perception, it can give rise to many famous sensory laws.

### 2.2.1 Relationship between the entropy model and other psychophysical laws

Magnitude estimation experiments are usually conducted at different intensity levels, each stimulus being held for a constant time. Thus, the duration of the stimulus \((t)\) is treated as a constant in the equation.

To derive Fechner’s law or Stevens’ law from the entropy model, let us set \(t = t' = \text{constant}\). Let \(\gamma = \beta / t'\), Eq. (2.1) becomes:

\[
F = \frac{1}{2} k \ln(1 + \gamma I^n)
\]  
(2.2)
When the given stimuli are strong, $\gamma l^n \gg 1$ and Eq. (2.2) becomes:

$$F \approx \frac{1}{2}k \ln(\gamma l^n) = \frac{1}{2}kn \ln(l) + \frac{1}{2}k \ln(\gamma) \quad (2.3)$$

Hence, the entropy model becomes Fechner’s law ($S = A \log(l) + K$) where $A = \frac{1}{2}kn$ and $K = \frac{1}{2}k \ln(\gamma)$

When the given stimuli are weak, $\gamma l^n \ll 1$. Using Taylor expansion on $\ln (1+x)$ where $0 < x \leq 1$, Eq. (2.2) becomes:

$$F \approx \frac{1}{2}k\gamma l^n - \frac{1}{4}k\gamma^2 l^{2n} + \text{higher order terms} \quad (2.4)$$

Retaining only the first order term:

$$F = \frac{1}{2}k\gamma l^n \quad (2.5)$$

The entropy model then becomes Stevens’ power law ($S = K l^A$) where $A = n$ and $K = \frac{1}{2}k\gamma$.

### 2.2.2 Model comparison to real data

In this section, the efficacy of the entropy model will be demonstrated by curve fitting.

#### 2.2.2.1 Magnitude estimation

In Figure 2.1 a), Eq. (2.2) was fit to the data of Luce and Mo’s study for weight perception.

Similarly, in Figure 2.2 b), Eq. (2.2) is shown to accurately describe the sweetness perception of sucrose measured by Moskowitz.
Figure 2.1 a) – The entropy model’s prediction on the pattern of weight perception. The original data was obtained from an experiment conducted by Luce and Mo (Luce & Mo, 1965).

Figure 2.1 b) – The entropy model’s prediction on sweetness perception of sucrose. The data was obtained from an experiment conducted by Moskowitz (Moskowitz, 1970).

2.2.2.2 Adaptation

The firing rate of a primary sensory neuron following application of a constant stimulus to its receptors decreases with increases in time. This is commonly known as the adaptation
phenomenon. It can also be observed across various stages of information processing, especially in the sensory domain.

During a sensory adaptation process, the intensity of the stimulus remains constant as duration increases. Hence, to derive the adaptation equation, we set $I$ from Eq. (2.1) to a constant, $I'$. Let $\lambda = \beta(I')^n$, Eq. (2.1) becomes:

$$F = \frac{1}{2} k \ln(1 + \frac{\beta(I')^n}{t})$$  \hspace{1cm} (2.6)

Figure 2.2 a) – Fitting of Eq. (2.6) to the adaptation pattern of hunting spider mecanoceptor (Bohnenberger, 1981); ‘d’ represents the stimulating amplitude ($I' = 0.395, 0.0975$)
Figure 2.2 b) – Fitting of Eq. (2.6) to the neural adaptation pattern of sugar receptor of blowflies (Dethier & Bowdan, 1984); each curve represents the measurements taken with different sugar concentrations ($I' = 1, 0.1, 0.01$)

Figure 2.2 a) & b) show the adaptation pattern of both the mechanoreceptor of hunting spiders and the sugar receptor of blowflies. In each curve, $I'$ from Eq. (2.6) takes on a different fixed intensity value while $t$ is the independent variable. These simultaneous curve fits further strengthen the robustness of the model over a wide variety of sensory modalities and biological organisms.

To sum up, a model like this has the potential of being a “unification model” for the biological sensory processes. In this thesis work, I would like to investigate the model’s capability of predicting SRT performance. It is to be hoped that the result will provide insights on the underlying mechanism of sensory and motor processes.

### 2.3 Motor physiology

Before the motor domain can be incorporated into the entropy model, it is important for us to quickly review some background knowledge on motor physiology.
During a sensory-motor reaction, the motor cortex governing production of appropriate motor responses receives input from the sensory cortex. A specific motor task requires balanced commands between excitatory and inhibitory inputs. This balance happens via the communication between the cerebral cortex, the thalamus and the brainstem. Signals are then carried through the spinal cord to the lower/peripheral motor neuron in the form of action potentials.

A group of motor neurons synapsing with one or more muscle fibers is called a motor unit. The synapsing points are commonly referred to as neuromuscular junctions. When the action potentials reach the distal end of the motor neuron, calcium ions flux into the neuron and cause the release of acetylcholine into the synaptic gap. These neurotransmitters result in depolarization of the muscle fiber and eventually cause calcium ions to be released to the muscle filaments. With the help of these calcium ions and ATP, the muscle filaments can properly contract to produce a motor response.

During this process, the action potentials can be summed to produce a stronger contraction. Hence, the strength of contraction is correlated with the firing rate of the motor neuron. This relationship is found to be very similar to the connection between stimulus intensity and sensory magnitude estimation mentioned above.

Furthermore, adaptation also occurs in the motor domain. Similar to the sensory adaptation shown above, the firing rate of the motor neuron also decreases over time at different stages along the motor pathway.

### 2.4 Sensory-motor integration

In addition to pure motor physiology, some studies chose to look at the big picture of sensory-motor integration. As opposed to having the higher brain regions as primarily “sensory” or “motor”, many neurons may occupy intermediate positions between the two extremes. The neuronal latency of such neurons is often studied alongside the corresponding reaction time (Lamarre et al. 1986; Spidalieri et al., 1983; Cook & Maunsell, 2002; Eifuku et al., 2004;
Thompson & Schall, 2000). More specifically, DiCarlo and Maunsell proposed a new method of investigation, which is to examine the covariance between these two variables (DiCarlo & Maunsell, 2005). The assumption is that only if the neurons are closely related to the transformation from sensory stimulus to motor response, will the covariance between their neuronal latencies and the reaction time be significant. Such method provides additional information about the circuits that underlie specific behaviors in SRT experiments.
3. An entropic Simple Reaction Time (SRT) model

3.1 Derivation of the SRT model from the entropy of the signal

In section 2, it was shown that the entropy model can give rise to a wide range of sensory laws. In this section, I will introduce the SRT law that was previously established from the original model (Eq. (2.1)).

Before examining the algebraic derivation, we will quickly review the fundamental assumptions of the entropy model. In section 2, we have discussed that according to the entropy conjecture, when a steady stimulus is presented, the sensory receptor’s entropy (uncertainty) level associated with the stimulus should fall over time. During an SRT experiment, a continuous and steady stimulus is presented and the subject is then asked to respond as quickly as possible. In order to derive the SRT equation, a key assumption has to be made. That is, reaction can only be triggered when sufficient information about the stimulus has been received, or when a sufficient level of entropy has been reduced. This reduction of entropy is hence \( H(I, t_0) - H(I, t_r) \). In this equation, \( H(I, t_0) \) corresponds to the entropy level at the beginning of stimulus presentation \((t_0)\) when the subject is most uncertain about the stimulus. \( H(I, t_r) \) corresponds to the entropy level at time of reaction \((t_r)\). We will call this difference between two entropy levels \( \Delta H \).

Given the above assumptions, Norwich et al have established an equation that predicts SRT performance from the original entropy theory (Norwich et al., 1989):

Recall in 2.2 that the entropy model states:

\[
F = k * H = k * \frac{1}{2} \ln(1 + \beta \frac{I^n}{t})
\]  \hspace{1cm} (3.1)
Given the $H$-function:

$$H = \frac{1}{2} \ln \left( 1 + \beta \frac{l^n}{t} \right) \quad (3.2)$$

We have:

$$\Delta H = H(I, t_0) - H(I, t_r)$$

$$\Delta H = \frac{1}{2} \ln \left( 1 + \beta \frac{l^n}{t_0} \right) - \frac{1}{2} \ln \left( 1 + \beta \frac{l^n}{t_r} \right) \quad (3.3)$$

Solving for $t_r$:

$$t_r = \left( \frac{1}{t_0 e^{2\Delta H}} - \frac{1 - e^{-2\Delta H}}{\beta l^n} \right)^{-1} \quad (3.4)$$

We take $\Delta H$ to be a constant threshold of information. Hence, $t_r$ is a function of $I$.

Let $t_{r_{\text{min}}}$ be the minimum possible value of $t_r$, which can be measured when intensity is indefinitely large ($I \to \infty$).

Hence, when $\beta l^n \to \infty$, the above equation becomes:

$$t_{r_{\text{min}}} = t_0 e^{2\Delta H} \quad (3.5)$$

Let $I_{\text{min}}$ be the minimum value of $I$ for which a response is possible (threshold value of $I$). As $I \to I_{\text{min}}$, $t_r \to \infty$.

Therefore, for $I = I_{\text{min}}$, we obtained from Eq. (3.4):

$$\frac{1}{t_0 e^{2\Delta H}} - \frac{1 - e^{-2\Delta H}}{\beta l_{\text{min}}^n} = 0 \quad (3.6)$$

Solving for $I_{\text{min}}$:

$$I_{\text{min}} = \left( \frac{t_0 (e^{2\Delta H} - 1)}{\beta} \right)^{\frac{1}{n}}$$
\( I_{\text{min}}^n = \frac{t_0 e^{2\Delta H}(1 - e^{-2\Delta H})}{\beta} \) \hspace{1cm} (3.7)

Introducing Eq. (3.5):

\[ \frac{I_{\text{min}}^n}{t_{\text{rmin}}} = \frac{(1 - e^{-2\Delta H})}{\beta} \] \hspace{1cm} (3.8)

Lastly, if we introduce Eq. (3.5) and Eq. (3.8) to the expression for \( t_r \) (Eq. (3.4)):

\[ t_r = \left[ \frac{1}{t_{\text{rmin}}} - \frac{1}{t_{\text{rmin}}} \left( \frac{I_{\text{min}}}{I} \right)^n \right]^{-1} \] \hspace{1cm} (3.9)

We can finally simplify the above equation to get the entropic SRT equation:

\[ t_r = \frac{t_{\text{rmin}}}{1 - \left( \frac{I_{\text{min}}}{I} \right)^n} \] \hspace{1cm} (3.10)

Based on Eq. (3.10), reaction time \( t_r \) is dependent on the value of stimulus intensity \( I \), along with three other model parameters \( (t_{\text{rmin}}, I_{\text{min}} \text{ and } n) \). It can also be observed from the equation that \( t_r \) decreases as \( I \) increases. This model property agrees well with the experimental observation. Furthermore, as \( I \) approaches infinity, \( t_r \) approaches \( t_{\text{rmin}} \), which is the minimum possible SRT that can be achieved when the stimulus intensity is indefinitely large. \( I_{\text{min}} \) represents the absolute minimum intensity that can be perceived by the subject’s sensory system. One detail worth noticing is that the exponent \( n \) is the same exponent from the sensory laws derived in section 2.

### 3.1.1 Model performance on real SRT data

Next, we will demonstrate the efficacy of the entropic SRT model by curve fitting to some real SRT data.
Figure 3.1 – Curve fits of auditory and visual SRT measurements using Eq. (3.10) (Chochole, 1940; Jaśkowski et al., 1994; Doma & Hallett, 1988; Gilden et al., 1966)
<table>
<thead>
<tr>
<th></th>
<th>$n$</th>
<th>$I_{\text{min}}$</th>
<th>$t_{\text{rmin}}$ (ms)</th>
<th>SSE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chochole (audition)</td>
<td>0.439</td>
<td>0.449</td>
<td>117</td>
<td>636</td>
<td>0.994</td>
</tr>
<tr>
<td>(sound pressure)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jaśkowski (audition)</td>
<td>0.569</td>
<td>0.0533</td>
<td>205</td>
<td>61.1</td>
<td>0.974</td>
</tr>
<tr>
<td>(sound pressure)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Doma &amp; Hallett (vision)</td>
<td>0.289</td>
<td>0.0333</td>
<td>149</td>
<td>218</td>
<td>0.999</td>
</tr>
<tr>
<td>Gilden (vision)</td>
<td>0.166</td>
<td>0.0567</td>
<td>129</td>
<td>1057</td>
<td>0.970</td>
</tr>
</tbody>
</table>

*Table 3.1 – Values of all SRT model parameters estimated using data obtained from experiments on audition and vision (Chochole, 1940; Jaśkowski et al., 1994; Doma & Hallett, 1988; Gilden et al., 1966)*

Based on the curve fittings, the value of $n$ (unitless) seems to have a range of 0.3-0.6 for auditory SRT and 0.1-0.3 for visual SRT. This pattern agrees relatively well with the values of Stevens’ exponent, which further strengthens the connection between the SRT law and the sensory law obtained using the entropy approach (Teghtsoonian, 1971; Teghtsoonian et al., 1975). The values of $t_{\text{rmin}}$ have a reasonable range of 100-200 ms for audition and vision. Its value is typically found with the order of magnitude of 100 ms and the exact range depends on the experimental methodology used.

<table>
<thead>
<tr>
<th></th>
<th>$n$</th>
<th>$t_{\text{rmin}}$ (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Audition</td>
<td>0.3 - 0.6</td>
<td>100 - 200</td>
</tr>
<tr>
<td>Vision</td>
<td>0.1 - 0.3</td>
<td>100 - 200</td>
</tr>
</tbody>
</table>

*Table 3.2 – Ranges of parameter “$n$” and “$t_{\text{rmin}}$” for audition and vision SRT experiments*

In addition, $I_{\text{min}}$ tells us the estimated absolute minimum intensity that can be perceived by the subject. It has the same units as the $I$ of the corresponding experiment.
3.1.2 Comparison between the entropy SRT model and Piéron’s law

In addition to the parameter estimation from the above curve fits, further evidence supporting the model’s efficacy is that Piéron’s law can also be obtained from the entropic SRT equation (Norwich et al., 1989)

To show this, let us consider the case where \((\frac{l_{\text{min}}}{I})^n \ll 1\), the denominator of the fraction on the right-hand side of the entropic SRT equation (Eq. (3.10)) can be expanded in a binomial series:

\[
[1 - (\frac{l_{\text{min}}}{I})^n]^{-1} \approx 1 + (\frac{l_{\text{min}}}{I})^n + \cdots \quad (3.11)
\]

Retaining only the first-order term, Eq. (3.10) then becomes:

\[
t_r \approx t_{rmin}[1 + (\frac{l_{\text{min}}}{I})^n] \quad (3.12)
\]

That is,

\[
t_r - t_{rmin} = (t_{rmin}l_{\text{min}}^n)I^{-n} \quad (3.13)
\]

This has the exact form as the Piéron’s law that we saw in 2.1.4.2, with \(t_r = RT\), \(t_{rmin} = t_0\), \(t_{rmin}l_{\text{min}}^n = \beta\) and \(n = \alpha\):

\[
(RT - t_0) = \beta I^{-\alpha}
\]

It can be concluded from the derivation that in the context of the entropy theory, the SRT equation and Piéron’s law share the same exponent. Since this exponent is the same exponent as found in Stevens’ power law, the model may suggest a connection between the exponents in these psychophysical laws.
3.2 Adding a constant motor delay

The entropy model has been derived using sensory considerations. However, there is a motor component of SRT which we have not yet included. In the following section, we will explore the entropic SRT equation to search for this missing component.

During an SRT experiment, a sensory receptor first receives the incoming stimulus which leads to the “perception” of the stimulus by the brain. This perception process is believed to be followed by a decision and a motor command generated in the CNS (Central Nervous System). Finally, the motor command is relayed by motoneurons and arrive at the muscle fiber which leads to muscle contraction. It is commonly believed that intensity levels influence the decision making process only (Gilden et al., 1966; Wilson & Lit, 1981). The motor component of SRT is generally seen as the motor neuron conduction time.

Hence, the first attempt taken by Norwich to incorporate the motor component is to define $t_{motor}$ as the constant delay required for reaction execution in the motor domain (Norwich, 1993). In fact, this method of separating the sensory and motor aspects has been employed by many theoretical studies of SRT (Piéron, 1913; Miller & Ulrich, 2003; Ollman & Billington, 1972; Luce, 1986)

By this conjecture, the SRT equation becomes:

$$ t_r = \frac{t_{rmin}}{1 - (\frac{Imin}{I})^n} + t_{motor} \quad (3.14) $$

Eq. (3.14) thus has four fitting parameters instead of three. To test the effectiveness of this new equation, let us fit it to the same sets of experimental data as before.
Figure 3.2 – Curve fits of auditory and visual SRT measurements using Eq. (3.14) (Chochole, 1940; Jaškowski et al., 1994; Doma & Hallett, 1988; Gilden et al., 1966)
<table>
<thead>
<tr>
<th></th>
<th>$n$</th>
<th>$I_{\text{min}}$</th>
<th>$t_{r\text{min}} \ (\text{ms})$</th>
<th>$t_{\text{motor}} \ (\text{ms})$</th>
<th>SSE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chocholle (audition)</td>
<td>0.000118</td>
<td>0.529</td>
<td>0.0226</td>
<td>96.5</td>
<td>340</td>
<td>0.997</td>
</tr>
<tr>
<td>Jaśkowski (audition)</td>
<td>0.000675</td>
<td>0.254</td>
<td>0.0549</td>
<td>194</td>
<td>52.4</td>
<td>0.978</td>
</tr>
<tr>
<td>Doma &amp; Hallett (vision)</td>
<td>4.66E-5</td>
<td>0.0371</td>
<td>0.0204</td>
<td>106</td>
<td>261</td>
<td>0.998</td>
</tr>
<tr>
<td>Gilden (vision)</td>
<td>1.52E-5</td>
<td>0.0642</td>
<td>0.0105</td>
<td>86.7</td>
<td>1106</td>
<td>0.969</td>
</tr>
</tbody>
</table>

Table 3.3 – Values of new model parameters estimated using the same data as Table 3.1 (Chocholle, 1940; Jaśkowski et al., 1994; Doma & Hallet, 1988; Gilden et al., 1966)

Based on the results above, although the curve fits in figure 3.2 seem to describe the data well, the estimated values of $n$ and $t_{r\text{min}}$ are clearly out of the expected range. More specifically, they are all compressed to be indefinitely small. This makes the first part of the equation negligible; $t_{\text{motor}}$ on its own accounts for majority of the SRT. It seems that simply adding a constant to account for motor SRT does not provide a satisfying result. In fact, it is as if with more parameters available, the performance of the new model deviates from the accepted physiological values of $t_{r\text{min}}$ and $n$.

This observation can be counterintuitive. One probable explanation is that three parameters are already sufficient to provide good prediction on SRT. Could it be possible that the original entropy SRT model (Eq. (3.10)) is already complete on its own?

### 3.2.1 SRT vs. body size

We have also examined other consequences of including a motor SRT time ($t_{\text{motor}}$). For example, if $t_{\text{motor}}$ consists mainly of motoneuron conduction time, it would depend on the body size of the subject. If this $t_{\text{motor}}$ is significant enough to be treated as a separate constant to the SRT equation, then the overall SRT must change based on the body size of the subject. This is because larger body size may correspond to longer motor delay which gives rise to longer SRT.
In order to evaluate this $t_{motor}$ conjecture, I chose to examine the relationship between body size and SRT performance. Once again, the assumptions are that if $t_{motor}$ is the motoneuron conduction time and if it really takes up a big part of SRT, then there should be a clear trend between subject’s body size and the measured SRT.

In our lab, we have conducted auditory SRT experiments with four lab members with varying body heights. The results are shown below:

<table>
<thead>
<tr>
<th>Body height (cm)</th>
<th>$t_{rmin}$ (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>184</td>
<td>129</td>
</tr>
<tr>
<td>176</td>
<td>233</td>
</tr>
<tr>
<td>169</td>
<td>226</td>
</tr>
<tr>
<td>167</td>
<td>125</td>
</tr>
</tbody>
</table>

*Table 3.4 – Comparison between body heights and the estimated values of $t_{rmin}$*

Since different individuals may have SRT curves of different shapes, we have decided to only compare the SRT value measured at highest stimulus intensity ($t_{rmin} (I \rightarrow \infty)$). We believe that this value best reflects the contribution of $t_{motor}$, as the sensory portion of SRT is compressed to be indefinitely small.

No difference was observed from our data set possibly due to a limited subject pool. This may suggest that $t_{motor}$, or the motoneuron conduction time, is not a significant part of the overall SRT. We also studied the relationship between nerve conduction time and body size. It is known that the larger the cross-sectional area of the nerve, the faster the conduction velocity and the shorter the conduction time (Kupa et al., 1995). Zaidman shows that the nerve size (cross-sectional area) is generally correlated with body height (Zaidman, 2009). This means that the taller the individual, the more likely for them to have faster conduction time. This may suggest that males on average with greater body heights will have faster $t_{motor}$ than females. However,
Gakhar found that both sensory and motor nerve conduction velocity is slightly faster for females compared to males, potentially due to hormonal influences (Gakhar, 2014). Rivner also argues that height is negatively correlated with conduction velocity, which is different from Zaidman’s finding (Rivner, 2001).

While it is difficult to make a definitive conclusion one way or another, the reasons discussed above make it difficult to see that the motor conduction time ($t_{motor}$) should be included in the manner suggested by Eq. (3.14). Consequently, we have decided to take other attempts at integrating the motor component to the original entropic SRT equation (Eq. (3.10)). Perhaps there are better ways to incorporate the motor SRT into the model.

### 3.3 Re-interpreting the SRT model

We have seen that the original entropic SRT equation gives accurate predictions for SRT measurements, while adding an extra term to the equation renders it ineffective\(^1\). Therefore, we suspect that the original entropic SRT equation may be complete on its own. Perhaps the motor component is already embedded in the equation.

If the entropic SRT equation does include the motor component, perhaps all we need to do is to re-interpret the model using new rules and frameworks. Our next attempt is therefore to develop a new theoretical basis which allows Eq. (3.10) to include both the sensory and motor aspects of SRT processing.

Before developing a new model interpretation, let us have a quick recap of the motor physiology. The motor command originates from the motor cortex and is then transmitted via motoneuron to

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\(^1\) Keep in mind that, although many previous studies have integrated the motor component of SRT as a constant term, the failure in doing so in this thesis work is merely a result of the fundamental properties of the entropy model itself. Unlike other SRT models, this entropic SRT model may contain properties that we do not fully understand.
the neuromuscular junction (NMJ). When the motor command reaches the motor end plate, acetylcholine is released to the NMJ gap to stimulate muscle fiber contraction.

To study the relationship between the entropy model and motor domain activity, let us first evaluate the predictions of the entropy model for several motor phenomena.

![Motoneuron firing rate adaptation](image)

*Figure 3.3 - Curve fit of motoneuron firing rate adaptation using the entropy adaptation model (Eq. (2.6)) (Desmedt & Godaux, 1978)*
Figure 3.4 - Curve fit of frog muscle end-plate current using the entropy adaptation model (Eq. (2.6)) (Magleby & Stevens, 1972)

Figure 3.5 - Curve fit of the relationship between force output vs. motoneuron excitation rate using the entropy model for magnitude estimation (Eq. (2.2)) (Petitjean & Bellemare, 1994)

From figures above, it seems like the entropy model does a reasonably good job at predicting the activity at the motor domain.
In the context of the entropy theory, one possible interpretation of this is that both the sensory and motor processing pathway follow a similar mechanism. The process for which information is sampled and received over time can also happen at the motor domain. This means that the framework of the entropy SRT model can be translated directly to the motor domain. Therefore, the equation remains the same while the interpretation is different.

Recall in 3.1, we saw that $t_{rmin} = t_0 e^{2\Delta H}$. We also stated in the derivation of the entropic SRT equation that the reduction of entropy for reaction to occur is $H(I, t_0) - H(I, t_r)$. Here, $H(I, t_0)$ corresponds to the entropy level at the beginning of stimulus presentation ($t_0$) when the subject is most uncertain about the stimulus. Therefore, $t_0$ is considered to be the amount of time it takes for the entropy level ($H$) to reach its maximum level in the beginning of stimulus presentation. However, if we are in the motor domain, the entropy now refers to the motor unit’s uncertainty associated with the incoming signal from the CNS. Hence $t_0$ is the time taken for the motor entropy ($H$) to reach the maximum value. Since many different stages exist in the motor pathway, there are perhaps several ways to re-interpret the entropic SRT model.

**Interpretation 1** - if the entropy level ($H$) is associated with the motoneuron stage, the motoneuron adaptation curve shown in figure 3.3 likely shows where entropy is reduced in the motor domain. $t_0$ is the time taken for signal to travel from the sensory receptor to the motoneuron, where the entropy level first starts to decrease.

The $\Delta H$ has to be re-interpreted as the information needed for the motoneuron to initiate a muscle response. After adapting through a critical amount of $H$, the motoneuron can elicit a response in the following stage (NMJ activation) to cause muscle contraction. This new framework of the entropy model could mean that the entropy level begins high when the motoneuron firing rate is rapid. It then diminishes over time as the firing rate slows down.

**Interpretation 2** - if instead, the entropy level ($H$) is associated with the muscle end-plate at the NMJ, the current adaptation curve shown in figure 3.4 likely represents where entropy is reduced
in the motor domain. $t_0$ is thus the time taken by action potentials (APs) to travel from the sensory receptor to the muscle end plate, where the entropy level first starts to decrease.

The $\Delta H$ has to be re-interpreted as the quantity of information to be received via neurotransmitters (Ach) transportation to the post synaptic terminal (muscle). The entropy level begins high as a high level of current was stimulated at the end-plate, but it soon diminishes as more Ach molecules bind to the receptors on the post synaptic side and the current level drops. As the entropy adapts through a threshold amount ($\Delta H$), the muscle fiber will be activated.

Additional attempts have also been made, such as modeling the flux of Ach molecules in the NMJ. However, it was later found that the time scale of Ach uptake is too short for this stage to be the rate determining step of the SRT processing pathway. That is, the time constraint of the NMJ mechanism limits its ability in governing the effect of different intensities on SRT.

**Interpretation 3** - if on the other hand, the entropy level ($H$) is associated with the muscle fiber activation stage, figure 3.5 shown above likely represents the equivalent of sensory input vs. output relationship in the motor domain. $t_0$ is thus the time taken by signal to travel from the sensory receptor all the way to the muscle fiber, where the motor entropy level first starts to decrease.

The $\Delta H$ has to be re-interpreted as the amount of information to be received in order to induce a well-coordinated muscle contraction. The entropy level may begin high as majority of muscle fiber is activated at the same time, but it soon diminishes as the muscle movement becomes coordinated and more fiber cease contracting. This phenomenon also gives rise to the force adaptation pattern observed in sustained muscle contraction.

**Interpretation 4** - “the cascade conjecture”$^2$ Everything listed above are re-interpretations of the model based on one particular stage of the motor processing pathway. But what if instead of

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$^2$ Note that the name “cascade” has been used by McClelland in his previous work on modelling SRT (McClelland, 1979). However, in this section, the term “cascade theory” is restricted to the cascade
thinking the entropic SRT equation as model of a single stage in the motor domain, we treat the entire process of reaction as one big cascade of many small sensory and motor stages?

If we assume that the process of signal transduction and transmission takes place at every level of the reaction time pathway, we can put together a cascade model that unifies different stages. An incoming stimulus is first perceived by the receptor. Next, the sensory neuron picks up the signal and action potentials are produced to innervate neurons downstream. The same process continues down the reaction time pathway until muscle activation. The assumption is that the stimulus has to be processed by the previous stage before being received by the next. The $\Delta H$ from the original derivation of the entropic SRT equation is then the collective information required for processing of all stages. This new framework could mean that entropy level is maximum at the initial sensory receptor stage. It slowly reduces as information is relayed from one stage to another. And eventually sufficient amount of entropy has been reduced at the muscle fiber such that a motor movement can be triggered to make a reaction.

To sum up, none of the above interpretations of the model framework can be fully proved without extensive modelling study and solid experimental backup, both exceeding the scope of this thesis. Therefore, instead of continuing with the theoretical work, we have decided to take an experimental approach.

In the next section, we shall verify the original entropic SRT equation through an experimental attempt that teases out the sensory and motor components. We will also discuss the bigger picture of the integration of sensory and motor processing pathways of SRT.

conjecture proposed under the context of the entropy theory. Interestingly, both “cascade theories” share the same view of the entire reaction process being composed of elementary processing stages.
4. **Separating the sensory and motor components of SRT**

In section 3.3, several attempts have been made to incorporate the motor component of SRT into the entropic SRT equation. However, a satisfying resolution has not yet been reached. In this section, I choose to explore the sensory and motor components of SRT experimentally. I will also attempt to establish the theoretical connection between the two components from the aspect of the entropy model.

4.1 **Motivation for the experimental study**

4.1.1 **Absolute Threshold (AT) vs Simple Reaction Time (SRT)**

An absolute sensory threshold refers to the absolute minimum intensity required for stimulus perception. Measurements of this threshold can be used to decode the underlying mechanism of sensory processing. During an experiment for absolute threshold (AT) detection measurement, stimuli with fixed duration but various intensities are presented. The minimum intensity needed for perception was measured and its value was found to depend on the duration of the stimulus.

On the other hand, during an SRT experiment, the stimulus is always presented with fixed intensity. The minimum amount of time taken for the participant to react is recorded.

In this case, the recorded time becomes the variable that depends on the stimulus intensity. Consequently, a similar time-intensity relationship exists between the AT and SRT experiments.

More specifically, in the AT experiment, stimulus duration can be treated as the time needed for the participant to register the stimulus at the corresponding threshold intensity, which I will refer to as the “sensory processing time”. The SRT experiment instead focuses on measuring the minimum time it takes for the participant to register the stimulus and make a motor response at the given intensity, which I will refer to as the “sensory + motor processing time”.

32
From this point of view, one can think of SRT as simply the time measured in AT experiment plus an additional component for the motor response. By comparing the sensory processing time with the sensory-motor processing time, it is easy to tease out these pathways separately. More importantly, the difference between these two time variables will help us understand whether the resulting “motor processing time” should be considered as a constant term of the SRT model. We believe that this experimental study will not only shine light on the connection between the sensory and motor pathways, but will also bring us closer to the goal of turning the entropy model to a unification model for both processes.

### 4.1.2 Deriving the AT model from the entropy model

In order to analyze and compare the results from both experiments using the entropy model, it has to be shown first that the same theoretical framework can model both AT and SRT results. We have seen the derivation of the SRT law in section 3. Another similar derivation was proposed by Norwich for modelling the AT detection performance (Norwich, 1993).

The entropic SRT equation (Eq. (3.10)) states that:

$$ t_r = \frac{t_{rmin}}{1 - (\frac{I_{min}}{I})^n} \quad (3.10) $$

Recall in 3.1, we derived Eq. (3.5):

$$ t_{rmin} = t_0 e^{2\Delta H} \quad (3.5) $$

Let us rearrange Eq. (3.10) while introducing Eq. (3.5):

$$ \left(\frac{I_{min}}{I}\right)^n = 1 - \frac{t_0 e^{2\Delta H}}{t_r} \quad (4.1) $$

Recall that an absolute threshold is the measurement of minimal intensity ($I$) required for perception as a function of $t$. Hence, we replace $t_r$ with $t$ to represent the duration of the signal.
We also replace \( I \) with \( I_{\text{thresh}} \), which is the measured threshold. In addition, \( I_\infty \) is the minimum threshold no matter how long the signal is presented. We will use it to replace \( I_{\text{min}} \) which is essentially the same variable. Eq. (4.1) becomes:

\[
\frac{I_\infty}{I_{\text{thresh}}} = (1 - \frac{t_0 e^{2n\Delta H}}{t})^{\frac{1}{n}} \tag{4.2}
\]

Or

\[
\frac{I_{\text{thresh}}}{I_\infty} = (1 - \frac{t_0 e^{2\Delta H}}{t})^{-\frac{1}{n}} \tag{4.3}
\]

When

\[ t \gg t_0 e^{2\Delta H} \]

We can expand \( \frac{I_{\text{thresh}}}{I_\infty} \) in a binomial series and drop terms of order higher than the first:

\[
\frac{I_{\text{thresh}}}{I_\infty} = 1 + \frac{t_0 e^{2\Delta H}}{nt} \tag{4.4}
\]

If we set the constant \( \frac{t_0 e^{2\Delta H}}{n} \) equal to \( a \):

\[
\frac{I_{\text{thresh}}}{I_\infty} = 1 + \frac{a}{t} \tag{4.5}
\]

We obtained an entropic AT equation that is identical to the Blondel-Rey law (Blondel & Rey, 1912).

We now have one unified theoretical approach to study both AT and SRT performance. It allows us to tease apart the role of the motor component from the SRT pathway. Since 

\[ t_{\text{rmin}} = t_0 e^{2\Delta H} \]

from the above derivation, we can establish the following connection between the parameters of the entropic AT & SRT equations:

\[
a = \frac{t_0 e^{2\Delta H}}{n} = \frac{t_{\text{rmin}}}{n} \tag{4.6}
\]
Hence, it remains to be shown that both experimental results can be precisely described by the two entropic equations derived from the model. Moreover, we hypothesize that for the same participant, the values of the estimated parameters can be cross-referenced according to Eq. (4.6).

In summary, we will conduct both the AT and SRT experiments with the same group of participants. These measured results will be cross-referenced and consolidated using predictions from the entropy model. This experimental study will enhance our understanding of the different components of SRT. It will also evaluate the potential unification property of the entropy model by testing the above model hypothesis.

4.2 Methods

4.2.1 Participants
To minimize interindividual variability, we recruited the same group of participants for both AT and SRT experiments. The whole experimental process took about 1.5 hours. This pilot study included a limited number of participants (6) for both experiments (4 males, 2 females; 20-28 years of age). A questionnaire was used to screen for healthy hearing. None of the participants had potential health issues or previous exposure to high levels of noise that may have affected auditory function.

All participants were informed of the purpose of the experiments, gave their written consent, and were paid for their participation. Procedures were approved by the Research Ethics Board (REB) of University of Toronto.

4.2.2 Sound level calibration
In audiometric testing, dB SL (Sensation Level) refers to the number of decibels by which the intensity level exceeds the individual’s hearing threshold. We conducted both the AT and SRT experiments using units of dB SL. This way, each participant’s hearing threshold had to be measured as the reference sound level for the actual experiments. We call this process the sound
level calibration procedure.

4.2.2.1 Experimental set-up and apparatus

The program for the sound level calibration procedure was written and executed in MATLAB on the experimenter’s laptop (ThinkPad T450s). The laptop was also used to generate the auditory stimuli. The stimuli were presented binaurally through an external soundcard (Focusrite Scarlett 2i4) and delivered to the participant via a pair of Audio-Technica ATH-M50x headphones. To ensure the integrity of the stimulus presented via the headphones, the voltage output patterns from the Scarlett 2i4 were examined using an oscilloscope (Tektronix TDS 210). The experiment was conducted in a sound-attenuated chamber at the University of Toronto, St. George campus. The experimental results were collected and analyzed using MATLAB.

4.2.2.2 Procedure

1000 Hz pure tone with duration of 500 ms and linear gates of 2 ms was used as auditory stimulus in this part of the experiment. According to the audiometric standard, the hearing threshold of a pure tone refers to the minimum intensity at which the participant can perceive the stimulus 50% of the time (American Speech-Language-Hearing Association, 2005). To track this level, we implemented a Bayesian adaptive psychometric method called QUEST (Watson & Pelli, 1983) using MATLAB. This QUEST algorithm allowed the stimulus intensity to converge to the level of 50% perception over a total number of 40 trials. More specifically, QUEST did this by calculating the stimulus intensity of the current trial based on the answer from the previous trial. Furthermore, the participant’s response was collected via the 2 Interval-Forced-Choice (2AFC) paradigm. This means that during each trial, the participant was prompted to listen to 2 tones, with one being the pure tone stimulus at near threshold level and the other one being completely silent. The order of presentation was generated randomly. The participant had to provide feedback on which prompted tone was the non-silent tone by choosing one out of the two choices. The duration of this whole process was approximately 10 minutes.
4.2.3 **AT experiment**

4.2.3.1 **Experimental set-up and apparatus**

The set-up and apparatus used in the AT experiment were the same as the set-up of the sound level calibration procedure.

4.2.3.2 **Procedure**

In this study, to measure the sensory processing time directly, we employed an alternative paradigm for conducting the AT experiment. Instead of evaluating the intensity at a given duration, we kept the intensity constant and measured the minimum duration needed for stimulus to be perceived by the participant\(^3\). This way, the measured threshold duration can be treated as the minimum “sensory processing time” at the given intensity. This contrasts with the SRT experiment, where the recorded reaction time can be seen as the “sensory-and-motor processing time”.

The AT experiment was conducted immediately following the sound level calibration process. 1000 Hz pure tone with linear gates of 2 ms was again presented binaurally. The participant was presented with stimuli of varying intensities (2, 3, 5, 10, 15, 20 dB SL). During each trial, upon the presentation of the stimulus, the participant was asked to indicate whether or not the tone was audible by selecting “Yes” or “No” as the answer (Yes/No paradigm)\(^4\).

The goal of this experiment was to measure the minimum duration required for the participant to perceive the stimulus at various intensities. We denote this minimum duration as the “threshold duration” of the stimulus. This threshold should allow the participant to perceive the stimulus

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\(^3\) I would like to express my gratitude to Dr. Bruce Schnéder for his suggestion on this alternative paradigm for conducting AT experiments

\(^4\) Since in the SRT experiment, the participant had to make a Yes/No decision prior to pressing the push button, we chose the Yes/No paradigm over 2AFC here to minimize the procedural difference between the two experiments.
50% of the time. Since a Yes/No paradigm was employed, the psychometric function that
describes the probability of perception of the auditory tone ranges from 50% to 100%. To track
the stimulus duration for which the participant can perceive 50% of the time, the 75% point of the
psychometric function has to be determined. The QUEST algorithm was again used to vary the
stimulus duration until the “threshold duration” at the 75% perception point was located.

Moreover, to minimize variation among each individual’s criterion of stimulus perception, all
participants were instructed to “respond only when you are almost absolutely certain”. Each of
the 6 intensity levels contains 40 trials. This section of the experiments took about 50 minutes to
complete.

4.2.4 SRT experiment

4.2.4.1 Experimental set-up and apparatus

The set-up and apparatus used in the SRT experiment for audio presentation were the same as
the ones used in sound calibration process and AT experiments (ThinkPad T450s, Focusrite
Scarlett 2i4, Audio-Technic ATH-M50x).

To measure the motor response time, we used a mechanical push button was used to detect motor
response from the participant. A digital-to-analog converter (Measurement Computing USB-
1608FS) was used to timestamp the auditory stimulus onset and the push button trigger
simultaneously.
4.2.4.2 Procedure

1000 Hz pure tone with linear gates of 2 ms was again presented binaurally. The participants’ SRT for the following stimulus intensities were measured: 2, 3, 5, 10, 15, 20 dB SL.

Two types of stimuli durations were used for the SRT experiments:

1. SRT experiment #1 – For each intensity level, the auditory stimulus presented had the same duration as the corresponding threshold duration measured in the AT experiment. We will refer to this as SRT experiment #1.

2. SRT experiment #2 – All auditory stimuli presented had a constant duration of 500 ms. Since typical values of SRT do not exceed 500 ms, this paradigm was used to ensure that the stimulus was still on when the motor response was being made. This is the classical method for conducting SRT experiments. We will call it SRT experiment #2.

Two separate sessions were conducted for the two types of stimulus durations. Each session
contained 60 auditory stimuli (6 intensities x 10 repeats) plus 10% of silent stimuli for catch trials. For each intensity block, the same stimulus was presented 10 times. The presentation order of different intensity blocks was determined randomly. The inter-stimulus duration was also randomly chosen between 1-3 seconds. For each session, the participant was asked to press the push button as soon as possible upon perceiving the onset of any auditory stimulus. No foreperiods, warning messages or feedback were provided.

The overall goal of this experiment was to determine the average SRTs of the participants for these different intensity levels. If the participant pressed the push button in the interval of 80 ms to 1000 ms with respect to the stimulus onset, an SRT was scored (Schröter & Ulrich, 2007). If he/she pressed the button more than once during that interval, only the timing of the first button press was scored. If no response occurred within this range, a miss was scored and would be not considered for SRT calculation. If the participant pressed the button outside of this range, an FA was recorded. All participants made no more than 2-3% false alarms. This section of the experiment took about 20 minutes to complete.

4.3 Results

4.3.1 Measurements from AT & SRT experiments

In the AT experiment, the participant was presented with stimuli of varying intensity levels and the goal was to measure the minimum stimulus duration required for perception. QUEST adaptive method tracked the 75% position on the psychometric curve constructed from the Yes/No response. In SRT experiment #1, the participant was presented with stimuli with threshold durations obtained from the AT experiment. In SRT experiment #2, the participant was presented with stimuli that had a constant duration of 500 ms. The second SRT paradigm is considered as a more standard SRT measurement procedure. We have plotted results measured from the above experiments for all participants in the following graphs:
Figure 4.2 – Comparison between the data obtained from the AT experiment and SRT experiments for all participants
The overall results of the AT experiment (black dots) showed a decreasing pattern as stimulus intensity increases. This is expected from previous studies. Similarly, the result from SRT experiment #2 (red dots) using the constant durations also shows a typical decreasing pattern found in previous SRT data. However, for most participants, the values measured from SRT experiment #1 (blue dots) appear to be relatively constant across the intensity scale compared to measurements obtained from SRT experiment #2 (red dots). This type of outcome has never been observed in any previous SRT studies. The unique pattern may suggest that stimulus duration also plays a crucial part in the SRT performance.

Note that error bars are only present in the SRT data, as each dot is averaged over 10 different trials. On the other hand, each black point in the AT data is a single point that is estimated by QUEST over a total of 40-50 trials. Due to time constraints, this procedure is not repeated for the AT experiment.

We can compare the AT & SRT results by treating them as “sensory” and “sensory + motor” processing times. To obtain the “motor component”, we subtracted the averaged AT measurements from the averaged SRT #1 & #2 measurements:

!["motor component" of SRT](image)

*Figure 4.3 – The difference between the averaged data obtained from AT experiment and SRT experiments*
The resulting time difference between STR #1 and AT measurements seems to increase in the beginning and eventually becomes constant at higher intensities. Whereas the time difference between STR #2 and AT measurements is relatively constant across the intensity range.

4.3.2 Curve fittings using the entropy model

4.3.2.1 SRT curve fittings

Traditionally, SRT experiments have always been conducted using constant stimulus durations. Hence, we chose SRT data obtained using the classical paradigm (SRT experiment #2) for model curve fittings and analysis. SRT measurements from each participant were fitted to the entropic SRT equation (Eq. 3.10):

\[ t_r = \frac{t_{rmin}}{1 - (\frac{I_{min}}{I})^n} \quad (3.10) \]
Figure 4.4 – Curve fitting results of SRT #2 data using the entropic SRT equation
Table 4.1 shows the estimated values of model parameters for each participant.

<table>
<thead>
<tr>
<th></th>
<th>$I_{min}$ (W/m²)</th>
<th>n</th>
<th>$t_{rmin}$ (ms)</th>
<th>SSE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S1$</td>
<td>0.482</td>
<td>0.847</td>
<td>209.647</td>
<td>364.119</td>
<td>0.970</td>
</tr>
<tr>
<td>$S2$</td>
<td>0.684</td>
<td>0.483</td>
<td>230.535</td>
<td>3396.379</td>
<td>0.978</td>
</tr>
<tr>
<td>$S3$</td>
<td>0.274</td>
<td>0.465</td>
<td>342.157</td>
<td>683.274</td>
<td>0.987</td>
</tr>
<tr>
<td>$S4$</td>
<td>0.299</td>
<td>0.368</td>
<td>230.564</td>
<td>1405.556</td>
<td>0.972</td>
</tr>
<tr>
<td>$S5$</td>
<td>0.345</td>
<td>0.461</td>
<td>236.820</td>
<td>1257.820</td>
<td>0.968</td>
</tr>
<tr>
<td>$S6$</td>
<td>0.0505</td>
<td>0.0209</td>
<td>35.130</td>
<td>5853.836</td>
<td>0.909</td>
</tr>
</tbody>
</table>

Table 4.1 – Values of all SRT model parameters estimated from curve fittings using the entropic SRT equation

4.3.2.2 AT & SRT curve fittings

We hypothesized that the entropy model has the potential of predicting both the sensory and the motor processes. The derivations of the SRT law as well as the AT law have been demonstrated respectively in 3.1 and 4.1.

\[ t_r = \frac{t_{rmin}}{1 - (\frac{I_{min}}{I})^n} \quad \text{– entropic SRT equation} \]

\[ \frac{t_{thresh}}{t_\infty} = 1 + \frac{a}{t} \quad \text{– entropic AT equation} \]

We have also seen that for the entropy model to correctly predict results from both experiments, the estimated parameters should be able to be correlated in this relationship:

\[ a = \frac{t_{rmin}}{n} \quad (4.6) \]
Recall that the entropic AT equation is derived from the SRT equation where $I_\infty$ is replaced with $I_{\text{min}}$. Hence, when performing simultaneous curve fittings for both entropic AT and SRT equations, we treated $I_{\text{min}}$ and $I_\infty$ as one parameter. Four parameters were estimated in total ($t_{\text{rmin}}, I_{\text{min}}, n$ and $a$). Results of the curve fittings are shown in figure 4.5.
Figure 4.5 – Simultaneous curve fitting results of the AT and SRT experiment #2 data using the entropic AT & SRT equations
The following table compares values of $a$ from the AT equation with values of $\frac{t_{rmin}}{n}$ obtained from the SRT equation. It can be observed that all pairs of parameters have similar orders of magnitude.

<table>
<thead>
<tr>
<th></th>
<th>$\frac{t_{rmin}}{n}$</th>
<th>$a$</th>
<th>$SSE$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S1$</td>
<td>27.5645009</td>
<td>67.6695</td>
<td>5584.499</td>
<td>0.976</td>
</tr>
<tr>
<td>$S2$</td>
<td>477.1179744</td>
<td>309.5612</td>
<td>3856.857</td>
<td>0.993</td>
</tr>
<tr>
<td>$S3$</td>
<td>319.78683</td>
<td>427.3592</td>
<td>9855.738</td>
<td>0.982</td>
</tr>
<tr>
<td>$S4$</td>
<td>170.5772004</td>
<td>274.9022</td>
<td>13172.523</td>
<td>0.967</td>
</tr>
<tr>
<td>$S5$</td>
<td>284.7225062</td>
<td>528.5098</td>
<td>2984.693</td>
<td>0.988</td>
</tr>
<tr>
<td>$S6$</td>
<td>1452.244821</td>
<td>5616.24</td>
<td>12323.252</td>
<td>0.964</td>
</tr>
</tbody>
</table>

*Table 4.2 – Values of $\frac{t_{rmin}}{n}$ and $a$ obtained from simultaneous curve fittings using entropic AT & SRT equation*
5. **Summary, discussion and conclusion**

5.1 **Thesis summary**

Before entering the discussion, I would like to present a brief overview of this research. In 3.1, we reviewed an equation for Simple Reaction Time (SRT) prediction that was derived from the original entropy model in 1989 (Norwich et al., 1989). However, we have seen that the entropy model was originally established as a sensory model. Ideally, a motor component should be integrated into the SRT equation. Traditionally, the motor component was always treated as an additional constant time by many reaction time studies (Piéron, 1914; Miller & Ulrich, 2003; Ollman & Billington, 1972; Luce, 1986). Hence, the first attempt taken by Norwich was to append this motor component as a constant to the end of the entropic SRT equation (Norwich, 1993). However, as seen in 3.2, the parameter estimation of the new SRT equation was unsatisfying and the model’s efficacy was severely diminished. In 3.2.1, we also explored the magnitude of motor conduction time by comparing the subject’s body height with his/her SRT data. Based on both experimental and literature results, no correlation was found between body size and SRT. Paradoxically, we have shown that the original entropic SRT equation is more than sufficient to give accurate predictions on SRT data (see 3.1 & 3.2). Consequently, we suspect that the motor component is already integrated as part of the equation. A re-interpretation of the original SRT equation is desired. We first chose to approach this problem from the aspect of motor physiology. In section 3.3, we made several attempts to trace the flow of information through the motor system to establish a new model framework. However, none of them can be fully substantiated or proved within the scope of this thesis.

To gain more understanding, we then took an experimental approach to validate the efficacy of the original entropic SRT equation. A unique experimental methodology designed involves conducting the Absolute Threshold (AT) and SRT experiments simultaneously with the same group of participants. The underlying assumption is that the AT detection time as measured in the AT experiment represents the sensory component of SRT. The SRT measured is possibly
equal to the sum of this sensory time plus the residual motor component. In 4.1.2, we demonstrate that the entropy model can also give rise to an entropic AT equation that predicts the AT detection time (Norwich, 1993). Hence, the robustness of the entropy model can be tested by fitting both experimental results to the entropic AT & SRT equations.

In the AT experiment, the times required to detect the stimuli were measured. SRT experiment #1 used this measured time as the stimulus duration. As shown in figure 5.1, the SRT data was relatively constant across various intensity levels. The difference between two time variables (SRT #1 - AT) increases with increasing intensity as presented in 4.3.1. SRT experiment #2 was conducted using a constant stimulus duration of 500 ms. The SRT data collected here now displayed a classical pattern. The difference between two time variables (SRT #2 - AT) remained constant regardless of the intensity level as seen in 4.3.1.

![Graph showing SRT experiment results](image)

*Figure 5.1 – Rough sketches showing qualitative results of the experiments*[^1]

[^1]: The sketches are only rough representations of the qualitative results obtained. They do not reflect the quantitative complexity in the experimental data.
5.2 Discussion

5.2.1 Entropy theory & estimated parameters

Classical SRT studies are always conducted using stimuli with constant durations. Because of this, we decided to use the data obtained from SRT experiment #2 for model analysis. Based on figure 4.4 from 4.3.2.1, we have seen that the entropy model can yield accurate predictions of the SRT results. In five out of the six participants, the estimated values of $t_{min}$ (200-300 ms) were found to be 100 ms more than the typical values measured in previous auditory SRT studies (100-200 ms). This is likely because the stimuli of our experiment were all restricted to the lower intensity range (0-20 dB SL). As a result, the minimum reaction time ($t_{min}$) was estimated to be much larger. In four out of the six participants, the values of $n$ were predicted to be around 0.3-0.6 which agrees well with the typical range found in previous auditory SRT studies.

Furthermore, based on the simultaneous curve fittings (figure 4.5) done with both entropic AT and SRT equations in 4.3.2.2, the entropy model seems to describe both experimental results well. To gain more confidence in this dual capacity of the entropic equations, the values of model parameters were calculated and compared in table 4.2. It can be seen that the values of $\frac{t_{min}}{n}$ closely resemble the values of $a$ for all participants and all pairs of parameters have similar orders of magnitude. This consistency of parameters suggests that for the same individual, the entropy model may be capable of predicting both the AT and SRT performances with the same set of model parameters.

One should keep in mind that aside from giving precise theoretical predictions, the entropic AT and SRT equations are both derived under the same assumptions of the entropy model. With minimal algebraic manipulation, both equations can be transformed to famous empirical laws like the Blondel-Rey law and Piéron’s law. This gives us more confidence in the completeness of the general entropy model itself. Perhaps the entropy model really has the potential of being a unified model for both the sensory and motor components.
Let us briefly reconsider the model interpretations that were proposed in 3.3. One similarity between these interpretations is that sensory perception and motor response are assumed to execute in a strictly serial fashion. But is this really how response is programmed neurophysiologically? Another aspect of our experimental results may help us understand more about this matter.

5.2.2 **Sensory & motor components – serial or parallel?**

The serial processing theory states that signal at one stage cannot be processed unless sufficient information from the previous stage has been obtained (Townsend & Fifić, 2004). Conversely, in the parallel processing model, there can be temporal overlap of functions across multiple stages. One stage begins to operate on a partial output of another stage that has not fully completed its activity. There has been a long, historical debate between two theories on both the theoretical and empirical levels. Investigating this is not a trivial matter, but the experiments we performed provided a possible approach.

The two paradigms of our experiments (SRT experiment #1 & #2) provided a unique perspective for probing these two theories of information processing. The SRT performance varies significantly between the two experimental paradigms. In SRT experiment #2, where the stimuli all have constant durations, the measured SRT decreases as intensity increases. This is a commonly observed pattern for all SRT studies. Nonetheless, when the perception time measured from the AT experiment was used as stimulus duration, the measured SRT was rather relatively constant across the intensity range.

Let us briefly examine the stimulus duration for two different paradigms. In SRT experiment #1, the stimulus duration can be taken as the threshold time required for stimulus perception at the given intensity. In SRT experiment #2, the stimulus was left on beyond this stimulus perception time. Recall that in the AT experiment, perception time falls drastically with larger stimulus
intensity. This falling pattern was only observed in the data of SRT experiment #2 and was absent in the constant SRT pattern collected in SRT experiment #1. It seems that the pattern of perception/reaction changes completely when the stimulus was kept on after “perception” had occurred. Perhaps after “perception” has occurred, the stimulus continues to influence the processing of both the perception and the motor pathway. This interpretation of the result implies that the reaction task processing may not be strictly serial.

5.3 Other literature

5.3.1 Sensory & motor components of SRT

The problem of teasing apart different processing stages of reaction task is not new. Back in the 19th century, Donders proposed the subtraction method as an indirect way of measuring different steps within the processing cascade (Donders, 1860). The subtraction method used different types of reaction time tasks to obtain perception, discrimination, response choice and motor production components. In the 1900s, psychologists also proposed the additive factors method that used different variations of choice reaction time tasks to calculate the time variants of individual stages. However, both methods have serious complications. For example, they both assume that the individual stages take place in a serial order and the overall reaction time is strictly the sum of the processing times of separate stages. The criticism of both methods as well as the discussion of serial vs. parallel processing are still being carried out to this day (Band & Miller, 1997; Miller & Low, 2001; Ulrich et al., 1999). However, there has been a growing amount of experimental evidence and theoretical models that support the parallel processing theory in reaction time tasks (Lindsay & Lindsay, 1966; Luce 1986; Miller & Ulrich, 2003).

In order to gather more evidence about the functional organization of the reaction programming pathway, contemporary electrophysiological methods were employed to directly measure time taken at each individual stage (e.g. sensory perception, stimulus registration, motor recruitment, muscle activation etc.). Direct comparison between the overall SRT and the latency of event-related potentials (ERPs) showed that intensity generally influences very early stages. More
specifically, scientists found that visual intensity had identical effects on SRT and on the latency of the N1 component of ERP (Gilden et al., 1966; Wilson & Lit, 1981; Jaśkowski et al., 1990). These findings suggest that the stages later than those reflected by the N1 component (which peaks at about 100–150 ms) are independent of stimulus intensity, yet other studies raised different viewpoints. For example, for auditory stimuli, Jaśkowski et al found effects of stimulus intensity on SRT to be larger than that on N1 latency (Jaśkowski et al., 1994). Similar results were also reported for visual stimuli (Kammer et al., 1999). These findings indicate that stimulus intensity is not restricted to an early processing level.

Other than using ERPs, physiologists have also examined the relationship between intensity and lateralized readiness potential (LRP) (Eimer & Coles, 2003; Leuthold et al., 1996; Miller & Low, 2001; Miller & Ulrich, 1998). LRP is a negative potential observed in the EEG activity prior to the initiation of a voluntary movement. Scientists have divided LRP into stimulus-locked LRP (S-LRP, relative to the stimulus presentation) and response-locked LRP (R-LRP, relative to the onset of response). Miller et al employed this approach to check the effect of the intensity for both visual and auditory stimuli using choice reaction time task (Miller et al., 1999). For visual stimuli, brighter signal resulted in a shortening of RT and an earlier S-LRP but had no effect on the R-LRP. This implied that the premotor processes are affected by stimulus intensity whereas motor processes are not. However, the results for auditory stimuli were rather uncertain. Neither S-LRP nor R-LRP onset was dependent on the loudness level. Yet, in a study performed by Jaśkowski et al in 2007, the same experiment was repeated for SRT tasks with several other minor methodological adjustments (Jaśkowski et al., 2007). Jaśkowski showed that both S-LRP and R-LRP onsets were influenced by the intensity of visual stimuli. With auditory stimuli, only S-LRP onset was found to be dependent on the intensity level. In addition, electromyography (EMG) and response force have also been measured as the output variable for the motor processing stage. The effect of intensity on the premotor and motor components was consequently determined.

Conflicting results were again obtained between visual and auditory modalities (Bartlett 1963, Allen & Sashin, 1960; Angel, 1973, Jaśkowski et al., 1995). In fact, numerous studies have proven that results seem to vary based on the sensory modality tested, especially for auditory and visual
stimulus. Miller et al gave a comprehensive overview of different studies and their results with respect to the two modalities (Miller et al., 1999). However, no definitive conclusion can be drawn from these outcomes.

In addition, a study reported by Heil et al also conducted AT and SRT experiments simultaneously but for a purpose different from ours (Heil et al., 2006). More specifically, they used AT and SRT experiments to study the mechanism that underlies threshold coding. Here, the classical SRT experiment is regarded as a reaction threshold detection experiment. Comparison was made between the reaction thresholds obtained from the SRT experiment and detection thresholds measured from the AT experiment. Heil et al found that minimum intensity required for motor reaction is always higher than minimum intensity required for stimulus perception. One explanation offered by the authors is that listeners may have some resistance to react. That is, they may need to accumulate more evidence before reaching the decision to press the key.

5.4 Future work and conclusion

There are many aspects that we would like to improve for our future study. Due to the scope of this project, the size of the participant group is limited to six. For future work, the same experiments can be repeated with a larger pool of participants to obtain higher confidence in the model performance. Furthermore, this study did not include complex analysis on False Alarm (FA) rates as all participants made no more than 2-3% false responses. For future work, a more careful approach will be taken to correct the data for FA. Possible methods include ANOVA analysis or race model correction (Ratcliff, 1993; Schröter et al., 2007; Tiefenau et al., 2006). In addition, the 2AFC paradigm for sound calibration process may have set the reference threshold excessively low relative to the Yes/No method. This can potentially diminish the effect of stimulus intensity on perception and reaction tasks. A future improvement could be to employ a Yes/No paradigm for the calibration step as well.
We believe that our work is the first in which the time components of sensory and motor processes are teased out using this unique combination of AT and SRT experiments. The two different SRT experimental paradigms (SRT experiment #1 & #2) may not provide a definitive conclusion on whether or not motor response component is influenced by the stimulus intensity. Nonetheless, it can be seen from other studies that resolution of this problem itself is not a trivial matter. The experimental results may depend on numerous factors such as sensory modalities or the methodological design of the experiment. However, we believe that our study has indeed provided a unique and promising perspective of tackling the complex nature of perception and response coding. More importantly, recall in 2.2, we have seen that the entropy model can generate accurate predictions for various sensory phenomena. Together with the results of this experiment, we have truly seen the potential of the entropy model as a general model that unites both the sensory and motor processes.
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(Original work published 1860)


Appendices

A.1 Derivation of the entropy model

The following model derivation was originally developed by Norwich in 1977 (Norwich, 1977).

Prior to deriving the model for sensory perception, let us first examine the mathematical definition of entropy. The original definition of entropy comes from Shannon’s work on information theory (Shannon, 1948). The entropy of a continuous random variable $x$ can be calculated through:

$$H = -\int p(x) \log p(x) \, dx \quad (A.1)$$

where $p(x)$ is the density function of the random variable $x$.

Given a stimulus presentation, the information obtained is the difference between entropy of the mixture of signal + noise and entropy of noise itself. Let us use $I$ to denote the potential information that can be received by the receptor:

$$I = H_{SN} - H_{N} \quad (A.2)$$

Suppose that a pure signal is described by $N(x; \mu_S, \sigma_S)$ and its obfuscating noise is described by $N(x; \mu_N, \sigma_N)$. The density function resulting from pure signal in the presence of noise is provided by the convolution:

$$p_{SN}(x) = \int_{-\infty}^{\infty} N(x - x'; \mu_S, \sigma_S) N(x'; \mu_N, \sigma_N) \, dx' \quad (A.3)$$

The result is a Gaussian density described by:

$$N \left( x; \mu_S + \mu_N, (\sigma_S^2 + \sigma_N^2)^{\frac{1}{2}} \right) \quad (A.4)$$

We can calculate the entropy of the normally distributed random variable $x$: 
\[ H = - \int_{-\infty}^{\infty} (2\pi \sigma^2)^{-\frac{1}{2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \ln \left( (2\pi \sigma^2)^{-\frac{1}{2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \right) \, dx \]

\[ H = \frac{1}{2} \ln(2\pi \sigma^2) \int_{-\infty}^{\infty} (2\pi \sigma^2)^{-\frac{1}{2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \, dx + \frac{1}{2\sigma^2} \int_{-\infty}^{\infty} (2\pi \sigma^2)^{-\frac{1}{2}} (x-\mu)^2 e^{-\frac{(x-\mu)^2}{2\sigma^2}} \, dx \quad (A.5) \]

And since

\[ \int_{-\infty}^{\infty} N(x; \mu, \sigma) \, dx = 1 \]

\[ \int_{-\infty}^{\infty} N(x; \mu, \sigma)(x-\mu)^2 \, dx = \sigma^2 \]

We get

\[ H = \frac{1}{2} \ln(2\pi \sigma^2) + \frac{1}{2} = \frac{1}{2} \ln(2\pi e \sigma^2) \quad (A.6) \]

Hence, Eq. (A.2) becomes:

\[ I = \frac{1}{2} \ln[2\pi e (\sigma_S^2 + \sigma_N^2)] - \frac{1}{2} \ln[2\pi e \sigma_N^2] \]

\[ I = \frac{1}{2} \ln[1 + \frac{\sigma_S^2}{\sigma_N^2}] (A.7) \]

Assuming the sensory receptor samples the incoming stimulus by drawing samples from this normally distributed population. The Central Limit Theorem states that if random samples of size \( m \) are drawn from a large population with mean \( \mu \) and variance \( \sigma^2 \), the sample mean is approximately distributed normally with mean \( \mu \) and variance \( \frac{\sigma^2}{m} \).

Therefore, Eq. (A.7) becomes:

\[ I = \frac{1}{2} \ln[1 + \frac{\sigma_S^2}{\sigma_N^2}] \quad (A.8) \]

Furthermore, assuming the rate of receptor sampling is constant, so that at time, \( t \),

\[ m = at \]
where \( m \) denotes the number of samples examined and \( \alpha \) is the constant sampling rate.

Since \( m = at \), we can then replace the \( m \) in Eq. (A.8) with \( at \) and replace \( l \) (potential information that can be received by the receptor) with \( H \) (current entropy level of the receptor):

\[
H = \frac{1}{2} \ln \left[ 1 + \frac{\sigma_S^2}{\alpha t \cdot \sigma_N^2} \right] \quad (A.9)
\]

One more fundamental assumption that we propose is:

\[
F = k H^6 \quad (A.10)
\]

where \( F \) is a perceptually related variable such as subjective magnitude or impulse frequency in a sensory neuron, \( k \) is a constant that is greater than zero and \( H \) is the entropy level associated with the stimulus at the receptor.

Substituting Eq. (A.9) into Eq. (A.10):

\[
F = k \frac{1}{2} \ln \left[ 1 + \frac{\sigma_S^2}{\alpha t \cdot \sigma_N^2} \right] \quad (A.11)
\]

Lastly, based on previous empirical studies within statistical physics (Jackson, 1968), we define the relationship between variance and measured intensity as:

\[
\sigma_S^2 \propto I^n
\]

where the constant \( n \) may differ among the modalities of sensation.

Setting \( \sigma_S^2 = \beta' \cdot I^n \) where \( \beta' \) is constant, introducing this relationship into Eq. (A.11):

\[
F = k \frac{1}{2} \ln \left[ 1 + \frac{\beta' \cdot I^n}{\alpha t \cdot \sigma_N^2} \right]
\]

By simplifying the equation, we obtained the final form of the entropy model:

\[\text{---}\]

\[\text{---}\]

\[\text{---}\]

\[\text{---}\]

\[\text{---}\]

\[\text{---}\]

\[\text{---}\]
\[ F = k \frac{1}{2} \ln \left[ 1 + \frac{\beta I^n}{t} \right] \]

where \( \beta = \frac{\beta'}{\alpha \sigma_n} \).

From this seminal equation, all empirical equations of psychophysics involving steady stimulus, \( I \), and stimulus duration, \( t \), may be derived (Norwich, 1993).
A.2 Testing system delay of SRT experiments

A reaction time experiment requires accurate and precise timing of events. We have designed and tested the experimental platform to minimize the effect of random and systematic errors.

Our initial experiments were programmed and conducted in MATLAB and in C. In both cases, delays on order of 500 ms were found indicating that high level programming environments do not have the level of accuracy or precision required for our experiments.

Next, we considered a hardware level solution to minimize these errors/delays. A multichannel USB data acquisition system (DAQ) was used to record both the changes in sound level as well as the button press. The DAQ (Measurement Computing USB-1608FS) allows for timestamping of both the events to microsecond accuracy.

Using an oscilloscope (Tektronix TDS 210), we were able to verify this setup. By recording the reaction time simultaneously through using the DAQ-based experimental platform and comparing it to the changes in voltage level with an oscilloscope, we were able to conclude that the DAQ platform can measure reaction time with less than one millisecond error, with no systematic delay introduced.