Pointing Models for Users Operating Under Different Speed Accuracy Strategies

ANONYMOUS AUTHOR(S)

ACM Reference Format:
Anonymous Author(s). 2024. Pointing Models for Users Operating Under Different Speed Accuracy Strategies. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11–16, 2024, Honolulu, HI, USA.* ACM, New York, NY, USA, 55 pages. https://doi.org/XXXXXXXXXXXX

1 INTRODUCTION

Pointing towards a target such as selecting an icon with a desktop mouse, is a fundamental interaction in HCI [7, 53]. Pointing *models* are commonly used to evaluate input techniques [53] and to design interfaces [10]. Pointing time is traditionally modeled using Fitts' law [17, 26, 53], often referred to as *movement time* (MT)

$$\mathrm{MT} = a + b\log_2(1 + \mathrm{D}/\mathrm{W}), \tag{1}$$

$$\equiv a + b\,\mathrm{ID}. \tag{2}$$

Here, W and D are the size and distance of the target, and $\mathrm{ID} = \log_2(1 + \mathrm{D}/\mathrm{W})$ is the index of difficulty. The parameters a and b are derived from empirical data [17, 53]. Fitts' law is considered to be a robust quantification of the speed-accuracy trade-off (SAT) in human movement [17, 53], that is valid across diverse populations, devices conditions and input modalities [53].

Fitts' law, however, provides only a partial account of the SAT:

- Fitts' law only describes a central tendency within the SAT, stating that a higher accuracy (smaller W) requires longer pointing times (higher MT). However, the variability of MT is significant, meaning some movements can be both faster and more precise than others. In short, Fitts' law handles a deterministic view of the SAT, and does not account for the distribution of movement times.
- Users/participants can choose their precision level for a given task[1] [34, 43, 61]. While the SAT concept allows trading speed for accuracy of vice-versa, Fitts' law does not explicitly incorporate user *strategy*. Instead, it assumes a task-defined accuracy.

The objective of this work is to provide a more comprehensive description of the SAT in human movement through parametric modeling. The modeling objectives are:

[1]For instance, participants of a Fitts' law experiment are often instructed to "be as fast as possible while not making too many errors" [53]

- The model should describe the entire distribution of movement times, not just the means as in Fitts' law. Consequently, MT is treated throughout this work as a random variable, the focus being on describing its distribution.
- The model should be parametric. While generative models could also learn these distributions (see *e.g.* [**?**] for a review on the topic), an explicit parametric approach offers greater adaptability to new contexts (*e.g.*, interaction devices, populations) and facilitates re-use by other researchers. Additionally, parametric models with relatively few parameters are generally more interpretable.
- One of the model's parameters should directly map to the concept of strategy representing a bias towards speed or accuracy in movement.

One might question the need for this work, given the long-standing success of Fitts' law. Why focus on aspects like movement time distributions and strategy? Regarding strategy, Guiard and Rioul [34] make a strong case for its consideration. They highlight that a trade-off between two variables, such as x and y, involves both the conservation of a quantity (*e.g.*, $x \times y$) and changes in the contributions of x and y. While Fitts' law addresses conservation, it neglects the changes. As for movement time distributions, there are practical advantages to examining distributions rather than just mean movement times that we will shortly come up to (subsection 4.2). At a high level, the argument is that "he who can do more can do less" — analyzing distributions retains more information than focusing solely on means, which inherently involves information loss.

To move beyond Fitts' law and its deterministic view of the trade-off between two quantities (*i.e.*, if one increases, the other decreases), we adopt a *statistical* approach with a probabilistic interpretation, focused on distributions. Instead of describing the relationship in absolute terms, statistical measures of association quantify how *likely* it is that one variable takes on a certain value given the value of another. To model these associations, we use conditional distributions, which provide a detailed account of how one variable's behavior changes across the range of another variable. Additionally, we employ bivariate copulas, mathematical tools that capture the full dependence structure between two variables, and allows expressing their joint distributions, which offers a more comprehensive representation of their relationship.

To better understand how strategy influences the SAT, we apply the aforementioned tools to data collected under three distinct experimental protocols (subsection 2.1). These protocols differ in how accuracy is defined: it may be explicitly task-defined, left to the discretion of the user, or involve a combination of both. In the task-defined condition, accuracy is dictated by the experimental design, leaving participants with limited flexibility in their approach. In contrast, the user-defined condition allows participants to balance speed and accuracy based on an instruction. The combined condition integrates elements of both, providing insight into how users adapt when both task and strategy constraints are at play.

Notations. $\mathcal{N}(\mu, \Sigma)$ refers to the (multivariate) Gaussian distribution with mean μ and covariance matrix Σ, $\mathcal{E}(\lambda)$ refers to the exponential distribution with mean λ, $\mathbb{E}[X]$ refers to the mathematical expectation of X, $\mathrm{Var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2]$ refers to the (population) variance of X. We use $X \sim \mathcal{D}$ to indicate that the random variable X is distributed following the distribution $\mathcal{D}$. We use R-style formulas to describe statistical models[2], for example, $A \sim X * Y + (1|Z)$ is a linear mixed effect model with random intercepts (per groups of Z values), with main effects X and Y, and with an interaction effect between X and Y.

[2]As used in R and in the Python statsmodels formula API.