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Investigating the Lead and Lag Times of Digital Freehands

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Preface

Previously, we have put in a considerable amount of effort to separate, identify, and then classify pen gestures from any given ink trace on the digital board. Those heuristics have been proven sound and efficiently fast, but lags in coherence when it comes to administering seriously ambiguous cases when both the domains for sketches and gestures are merged. When earlier, we analysed data solely from its raw repercussions, we now observe the same data with an additional temporal viewpoint.

1 Introduction

This report presents the mechanics behind Ingrid (our Ink Agent) as it sifts through the lead and lag times of each ink component perceived from the writing environment. Ingrid returns the probability that an ink component is in fact a symbolic Trace that forms part of a free-hand sentence or a composite freehand drawing. It draws this hypothesis from the bivariate normal density of the joint distribution between the lead and lag times obtained from our statistical samples contributed by various different styles of freehand writings.

We highlight the techniques of our experiments in the next sections in determining the four categories of ink components and how they are used to assist Ingrid's decision making in classifying new ink components. We also include a proposal of combining this temporal method with a spatial analysis that can be made useful in detecting multiple-stroke gestures while still maintaining the subtle relationship between symbolic Traces and command Gestures.

2 Temporal Relationships in Digital Freehands

In preparing for our experiments, we focused on establishing probabilistic conjunctions in freehand writings (which we considered as distinctively represented ideas from a set of written Traces) based solely on the lead and lag times between pen events. This tracks the nature of which people write and express ideas; be it in alphabetical sentences or graphical illustrations.

Traces on the digital board group together to form what we perceive as *freehand writings* or *freehand drawings*.

We define an *ink Trace* as the actual rendered graphics of a particular handwritten trace we see on screen, and an *ink component* as the 'data construct' manipulated by Ingrid (and any other application programs) while in memory.

2.1 Freehand Writings

Each Trace, resulting from a pair of successive pen-down and pen-up events, written on a tablet can be categorised in terms of the timings noted for;

- the *duration* of the Trace,
- its *lead*-time, and
- its *lag*-time.

Lead-time refers to the time taken before an ink Trace is scribed, and lag-time refers to the time taken after an ink Trace is scribed. This is illustrated in Figure 1.

For a set of contiguous ink components $S_j = \{c_0, c_1, c_2, \ldots, c_n\}$ in a freehand sentence made up of n traces, we note that the lag-time for the i^{th} component is exactly the same as the lead-time of the $(i+1)^{th}$ component; i.e. $\texttt{lag}(c_i) = \texttt{lead}(c_{i+1})$. Consequently, the timings that separate one set of ink components apart from another are the first lead-time $\texttt{lead}(c_0)$ and the last lag-time $\texttt{lag}(c_n)$ in S_j. These times are significantly longer than their in-between neighbours c_1 to c_{n-1}.

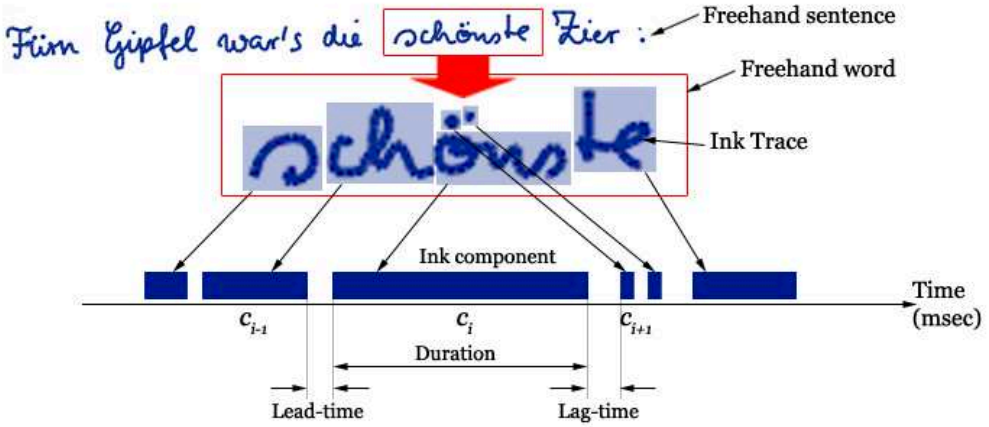

Figure 1: Splitting up freehand writing into its ink components on the time line.

Most people write rather fast such that the time intervals between intermediate ink components in one freehand word is very short. If we observe a *complete* freehand sentence made up of a group of freehand words, we can categorise each ink component within those words into one of the following four groups:

- **Beginnings** – Ink components found at the *start* of a freehand word;
- **Endings** – Ink components found at the *end* of a freehand word;
- **In-betweens** – Ink components found in the *middle* of a freehand word; and
- **Stand-alones** – Disjointed ink components.

The groups differ in the demarcations of their lead and lag times, and as such, provide for a way a pervasive system can identify them. Other forms of freehand writings include mathematical equations, alphabets or characters of various languages, and signatures.

2.2 Freehand Drawings

Similar to freehand writings, freehand drawings are also made up of composite sets of ink Traces. Here, the diagrams formed on screen are symbolically represented ideas of the writers' that we term as freehand shapes. Often, when using the digital whiteboard as a medium of conveying concepts to audiences, we include hand-drawings (illustrations) made up freehand shapes alongside any writings we may already have.

Collectively, a set of freehand shapes is the equivalent of freehand words. As such, the ink components formed by the freehand shapes, when observed by their lead and lag times, can also be classified as *beginnings*, *endings*, *in-betweens*, or *stand-alones*. Figure 2 highlights this preconception.

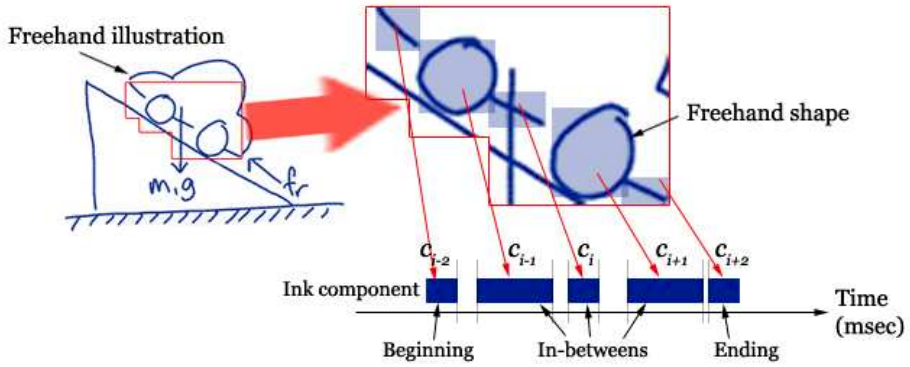

Figure 2: Splitting up freehand drawing into its ink components on the time line.

Completing this ontology, we further categorise other symbolic forms such as flow charts, state transition diagrams, and artistic and graphical illustrations as freehand drawings.

2.3 Stand-alone Components and Gestures

The temporal relation that singles out stand-alone components (and freehand gestures) from their continuous writing and drawing counterparts is the "longer-than-average" lead and lag times of a single-stroke ink Trace, as shown in Figure 3. In this case, there is a pause period between samplings of ink components that results in significantly longer lead *and* lag times.

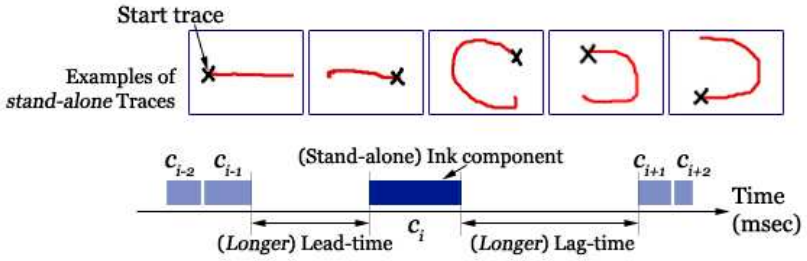

Figure 3: Stand-alone ink components that can be interpreted as a possible gesture.

As we will demonstrate in a later section, these stand-alone components do not occur as often as we would have predicted. And even when it does occur, the probability of the stand-alone component being a symbolic Trace is higher than it being a command Gesture.

It is not very often that we see people gesturing to a control system in the middle of writing a sentence or drawing a diagram. So we can anticipate, rather convincingly based on the lead and lag times obtained, that the latest ink component might be more of an instance of a Trace, rather than a Gesture.

In pursuit of standardising a suitable time-out period, we decided to set the upper limit of both the lead and lag times to 1500 msec, in retrospect after some initial testing. That is to say, if an observed (lead or lag) time exceeds this period, we immediately consider it as "significantly long" and record it as 1500 msec.

3 Sampling the Various Styles of Freehands

We tasked a few people at our institute to write sample scripts on a Wacom PL-550 tablet. These scripts are purposely designed to underline the various forms of symbolic Traces discussed in the previous section as freehand writings and freehand drawings. They constitute paragraphs from a book, mathematical equations, flow charts, state transition diagrams, technical drawings, artistic illustrations, and personal signatures.

Our participants all have their own distinctive styles of writing, some left handed while others right handed, differing in the way the strokes and curves are written. They each have different speeds of writing that seem to dictate the way the legibility and clarity of their compositions. These writings of several thousand traces are saved as InkML files (based on W3C's InkML standards [8]) that are then further scrutinised into one of the four ink component categories as beginnings, endings, in-betweens, or stand-alones.

4 Categorising Ink Components

Every single ink component retrieved from the InkML files are observed by their lead and lag times to be classified into one of the four predefined categories. We did this manually for the first 1,000 Traces in order to obtain the estimated timing distributions – the mean μ and standard deviations σ of the lead-lag times for all four categories – which are necessary to automate the entire process of scrutiny. The final values of which are shown in Table 1.

In milliseconds	**μ lead-time**	**μ lag-time**	**σ lead-time**	**σ lag-time**
Beginnings	1297.95	205.86	635.32	358.66
Endings	218.63	1303.45	370.90	602.34
In-betweens	194.31	200.11	356.78	372.56
Stand-alones	1227.87	1236.92	733.94	764.50

Table 1: Tabulated mean and standard deviations of the four categories with respect to the lead and lag times.

The values above are then entered into our analyser program that uses the following heuristics to automatically classify all other ink components. Where *b* refers to *beginnings*, *e* refers to *endings*, *i* refers to *in-betweens*, *s* refers to *stand-alones*, and κ as the scaling factor:

$$\text{Classify } [c_g\ (t_{\text{lead}}, t_{\text{lag}})] = \begin{cases} \text{Class } (b) & \text{, if } t_{\text{lead}} \geq \mu_{b_\text{lead}} - \kappa.\sigma_{b_\text{lead}} \text{ AND } t_{\text{lag}} \leq \mu_{b_\text{lag}} - \kappa.\sigma_{b_\text{lag}} \\ \text{Class } (e) & \text{, if } t_{\text{lead}} \leq \mu_{e_\text{lead}} + \kappa.\sigma_{e_\text{lead}} \text{ AND } t_{\text{lag}} \geq \mu_{e_\text{lag}} - \kappa.\sigma_{e_\text{lag}} \\ \text{Class } (i) & \text{, if } t_{\text{lead}} \leq \mu_{i_\text{lead}} + \kappa.\sigma_{\text{e_lead}} \text{ AND } t_{\text{lag}} \leq \mu_{i_\text{lag}} + \kappa.\sigma_{i_\text{lag}} \\ \text{Class } (s) & \text{, if } t_{\text{lead}} \geq \mu_{s_\text{lead}} - \kappa.\sigma_{\text{s_lead}} \text{ AND } t_{\text{lag}} \geq \mu_{s_\text{lag}} - \kappa.\sigma_{s_\text{lag}} \end{cases}$$

Here, the scaling factor is defined as $\kappa = 2\sigma/\sqrt{n}$, for n number of samples.

However, there are times when these heuristics are not able to categorise ink components due to the overlapping of ranges. We give a range-diagram in Figure 4 to illustrate this problem. Whenever this happens, the analyser program stops and prompts for guidance.

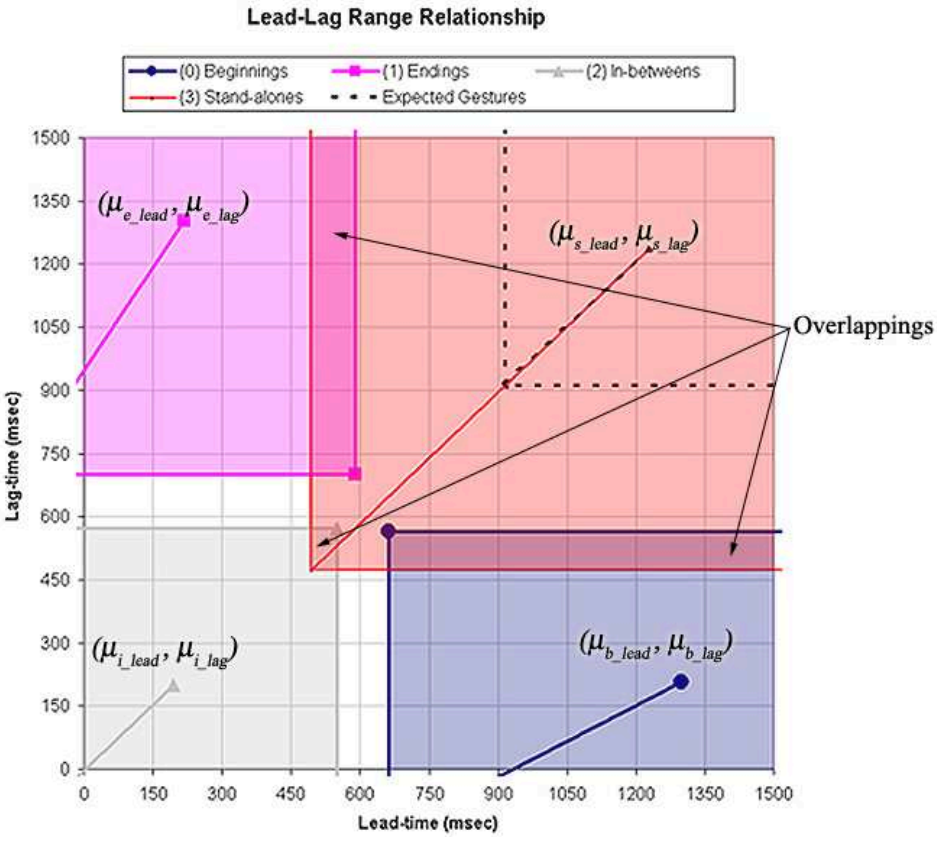

Figure 4: Range-diagram depicting the four overlapping categories.

Over time and after giving numerous suggested guidance, we noticed certain patterns emerging at every occurrence of our manually adjusting the misclassifications.

- That, if the previous ink component was categorised as *in-betweens*, then the current ink component should also be *in-betweens*.
- That, if the previous ink component was categorised as *beginnings*, then the current ink component should be *in-betweens*.
- That, if the previous ink component was categorised as *stand-alones*, then the current ink component should be *beginnings*.

Naturally, we incorporated the three additional rules above into our analyser program, kicking off if and only if the main classifier heuristics fail. This dramatically drops the number of failures and misclassifications.

5 Correlating the Lead and Lag Times

The classification process in Section 4 tags each ink component to one of the four designated categories. We noted a strong correlation between the lead and lag times amongst the ink components with respect to them being either beginnings, endings, in-betweens, or stand-alones.

5.1 Regional Areas

A follow-up to Figure 4, the scatter-plot diagram in Figure 5 illustrates the actual spread of all the tagged ink components in coordinate relation to their individual lead and lag times.

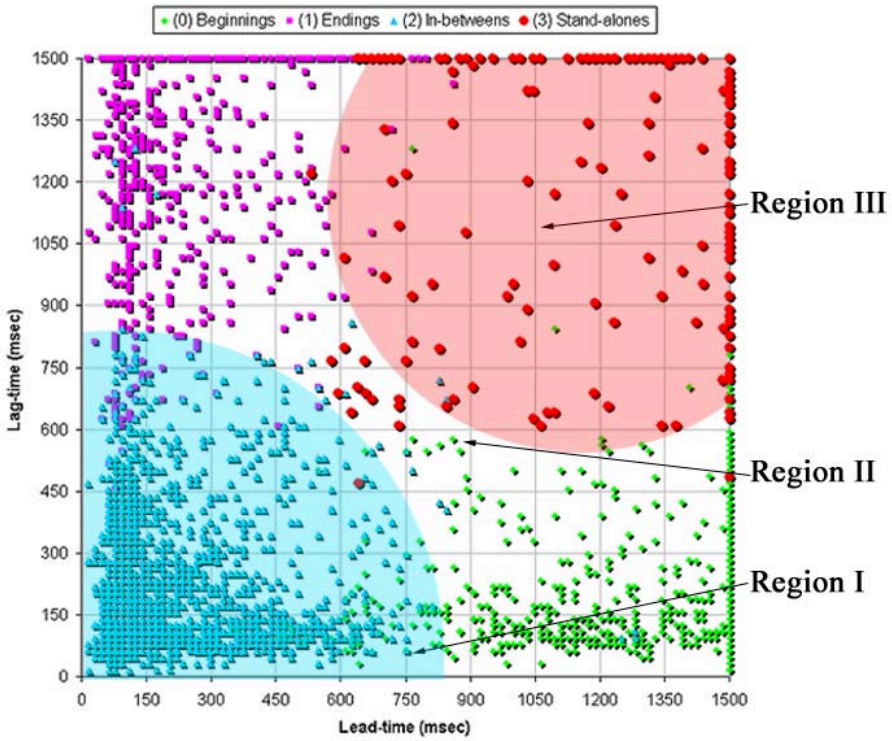

Figure 5: Scatter plot of 9570 pairs of categorised ink components.

We observe three main regions of clustering from the above scatter-plot – the 'near-neighbours' in Region I (made up mainly of the *in-betweens*), the 'extremes' in Region II (made up mainly of the *beginnings* and *endings*), and the 'solitaries' in Region III (made up mainly of the *stand-alones*). The tightness of the clustering decreases as we traverse the plot from Region I towards Region III; i.e. where Region I is very tightly clustered, the obvious sparseness in Region III suggests a huge variety of styles written for the stand-alone Traces.

The outline of each regional curve is the estimated resulting decision surface separating the samples between the stand-alones (Region III) and the non-stand-alones (Regions I and II). Their attached correlation coefficients r to Regions I, II and III are **0.7699**, **0.4819**, and **0.1230** respectively. Here, r is the measure of strength of the linear relation between the lead and lag time variables where the magnitude of r indicates the strength of a linear relation (i.e. a value r close to zero means that the linear association is weak), and is calculated with Equation 1, where X refers to the lead-time and Y refers to the lag-time variables.

$$r = \frac{S_{XY}}{\sqrt{S_{XX}}\sqrt{S_{YY}}} \tag{1}$$

where $S_{XY} = \sum (x - \bar{x})(y - \bar{y})$, $S_{XX} = \sum (x - \bar{x})^2$, $S_{YY} = \sum (y - \bar{y})^2$.

5.2 Categorical Distributions

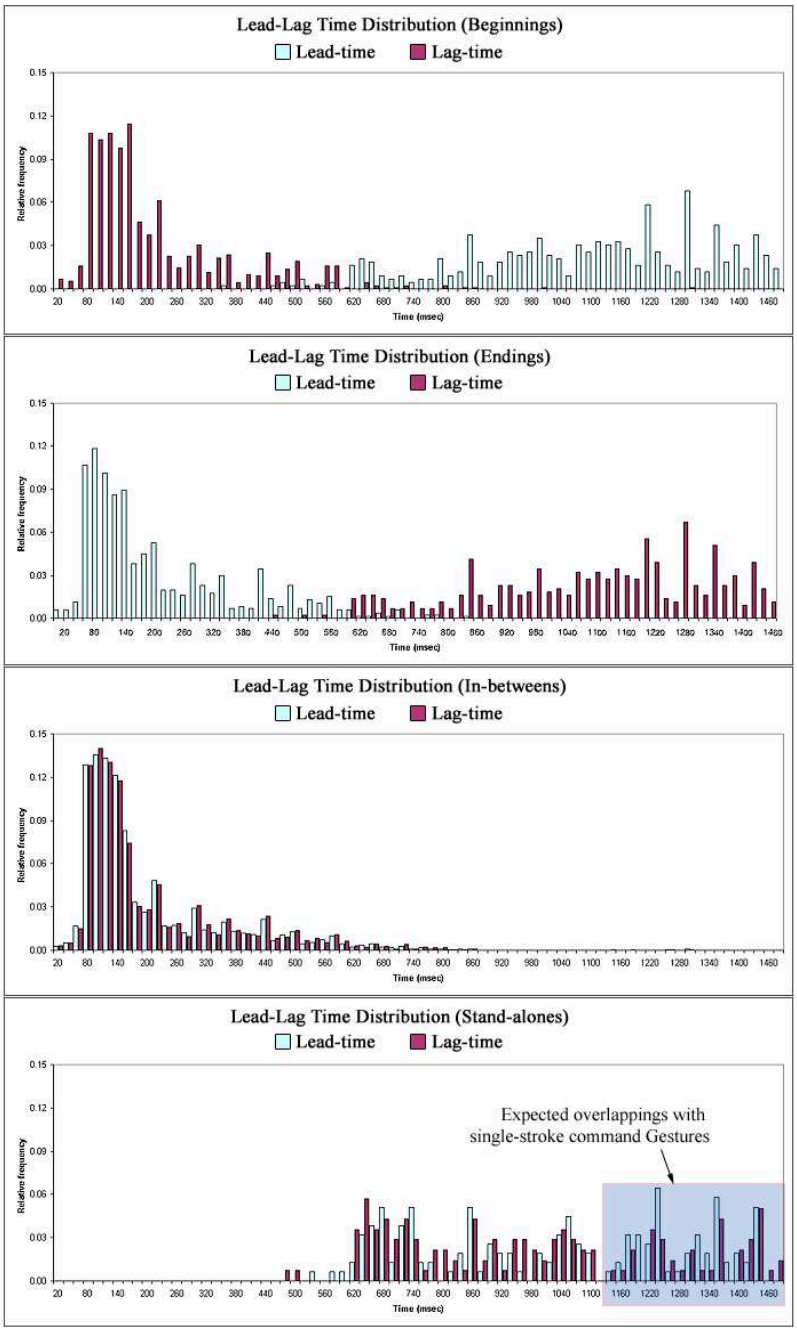

Figure 6: Lead-lag time distributions for beginnings, endings, in-betweens, and stand-alones.

From all 9750 pairs of samples (of ink components), we tabulated their relative numbers and found the percentage distributions for all four categories. Figure 6 depicts each of those cate-

gories, while separating the individual distributions of the lead and lag times. The graph confirm the scatter-plot diagram in Figure 5 and prepares the essential grounds for our further investigation in finding out the chances that an ink component is a symbolic Trace, given its lead and lag times.

The stand-alone distribution graph is expected to be of a significant interest to us, as it tells the slim probability whenever an ink component is not a symbolic Trace. We know that this graph alone is not sufficient enough to strongly predict any user intentions each time we receive a stand-alone ink component. However, combined with the other three graphs, we help reduce the number of processes needed to continuously track all freehand writings on the perceptual user interface environment.

6 Studying the Bivariate Data

When two traits are observed for the individual sampling units and each trait is recorded in some qualitative categories, then the joint behaviour of two random variables, X and Y from each of the traits, is determined by the cumulative distributive function,

$$\begin{aligned} F(x,y) &= P(X \le x, Y \le y) \\ &= \int_{-\infty}^{x} \int_{-\infty}^{y} f(u,v)\, dv\, du, \end{aligned}$$

derived directly from the fundamental theorem of multivariate calculus [3, 6]. It follows that,

$$f(x,y) = \frac{\partial^2}{\partial x\, \partial y} F(x,y)\,.$$

The graphs obtained in Figure 6 hint that our distributions of the lead and lag times across all four categories are varying "Normally", with μ_x = **462.0059**, μ_y = **462.2614**, σ_x = **682.0767**, and σ_y = **682.6080**, where x and y refer to the lead- and lag-time variables respectively.

We find it advantageous to know the joint relation between the lead and lag times of each ink component for making obvious generalisations in the future. A lookup probability table constructed from the current samples of categorised ink components, following a bivariate normal density, is expected to expedite our mission of finding the quick probability for a symbolic Trace to remain in its own entity. Equation 2 describes this density function, and Figure 7 illustrates the lookup table graphically.

$$f(x,y) = \frac{1}{2\pi\, \sigma_x\, \sigma_y \sqrt{1-\rho^2}} \exp\left[-\frac{z}{2(1-\rho^2)} \right] \tag{2}$$

$$\text{where } z = \frac{(x-\mu_x)^2}{\sigma_x^2} + \frac{(y-\mu_y)^2}{\sigma_y^2} - \frac{2\rho(x-\mu_x)(y-\mu_y)}{\sigma_x\, \sigma_y}, \tag{3}$$

$$\text{and } \rho \equiv cor(x,y) = \frac{\sigma_{xy}}{\sigma_x\, \sigma_y}$$

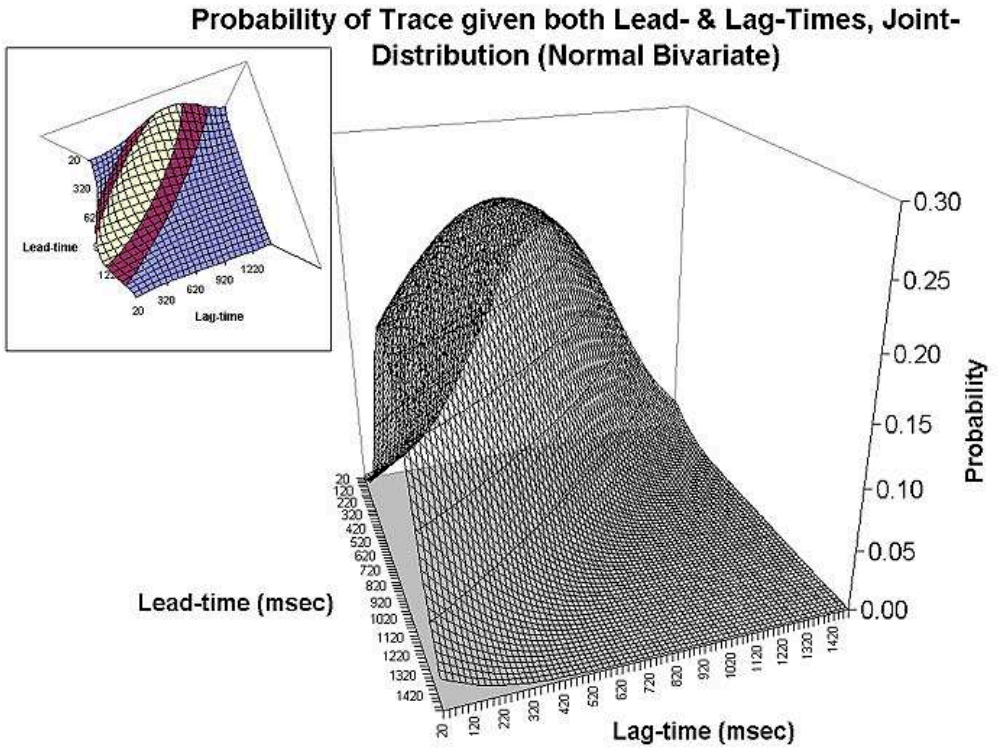

Figure 7: Joint distribution via the normal bivariate density.

For every section on the surface in Figure 7 that gives a high probability that an ink component should be a symbolic Trace, there are other sections on the surface that depicts otherwise. These sections confirm our scatter-plot diagram in Figure 5, and are the composite distributions of all the graphs in Figure 6.

The next section details the use of the graph in Figure 7 through the formal formulation of our statistical hypotheses in making proper inferences of the population samples.

7 Statistical Acceptance

Broadly speaking, the goal of testing statistical hypotheses is to determine or conjecture about some features of the population, which is strongly supported by the information obtained from the sample data. Based on key statistical concepts in the context of determining the best solution for our problem definition, we establish the alternative hypothesis H_1 and its nullifying opposite H_0 as stated below.

H_0: "That an ink component is NOT a symbolic Trace".

H_1: "That an ink component IS a symbolic Trace".

Where testing each hypothesis is carried out as follows, where *X* and *Y* refer to the lead- and lag-time variables respectively:

H_0: $\overline{X} \geq \mu_x, \quad \overline{Y} \geq \mu_y$

H_1: $\overline{X} < \mu_x, \quad \overline{Y} < \mu_y$

7.1 Test Statistic

Our test statistic refers directly to the joint-distribution described in Equation 2 (and its Figure 7 equivalent), so that Equation 3, the *Z*-test, forms the rejection criteria needed for a test level of significance $\alpha = 0.05$ (and that $\alpha/2 = 0.025$). Figure 8 demonstrates this notion from two cross-sectional views of the normal bivariate density curve.

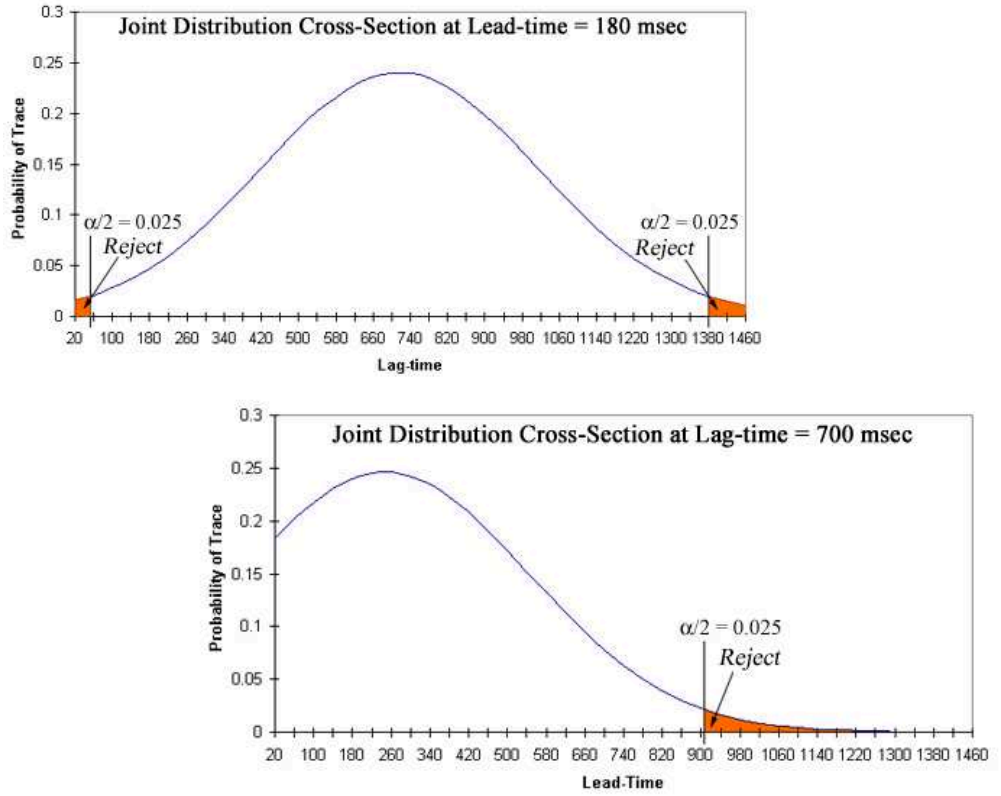

Figure 8: Cross-sectional view of the joint distribution of the normal bivariate density at lead-time = 180 msec and lag-time = 700 msec respectively.

We accept H_1, if and only if $R{:}|Z| \geq Z_{\alpha/2}$, where R refers to the rejection regions highlighted in Figure 8, and $Z_{\alpha/2} = Z_{0.025}$ is the boundary of acceptance on the joint distribution of the normal bivariate density graph shown in Figure 9. Otherwise, we reject H_1 and claim H_0 that an ink component $c_g(X = t_{lead}, Y = t_{lag})$ shall not be considered as a symbolic Trace.

7.2 Inferring the Bivariate Data

Plugging in the values of $\mu_x = 462.0059$, $\mu_y = 462.2614$, $\sigma_x = 682.0767$, and $\sigma_y = 682.6080$ for every time-step of *X* and *Y* from 0 to 1500, we obtain the entire region of acceptance (and rejection) on our bivariate surface. The darkened regions in Figure 9 are the areas for 'rejection' while the lighter region is the area for 'acceptance'. Figure 9 is made to correspond directly to our lookup table, with the input parameter c_g (t_{lead}, t_{lag}) and retrieving from the table an output probability of whether any ink components should be considered as symbolic Traces given its lead and lag times (i.e. P (Trace | c_g (t_{lead}, t_{lag}))), with an attached H_1 (strong acceptance) or H_0 (strong rejection).

Two examples are given in Figure 9. The first, with an input parameter of c_1 (1377, 1281) gets a probability value of $P = 7.38 \times 10^{-08}$ and recommended for 'rejection'. This means that

the likelihood of the ink component c_1 being a symbolic Trace is very slim, and further tests should be made to check if we could indeed upgrade it to a command Gesture.

The second, with an input parameter of c_2 (309, 1011) receives P = 0.1164 and recommended for 'acceptance'. This is a clear-cut case that the ink component c_2 should definitely be considered as a symbolic Trace.

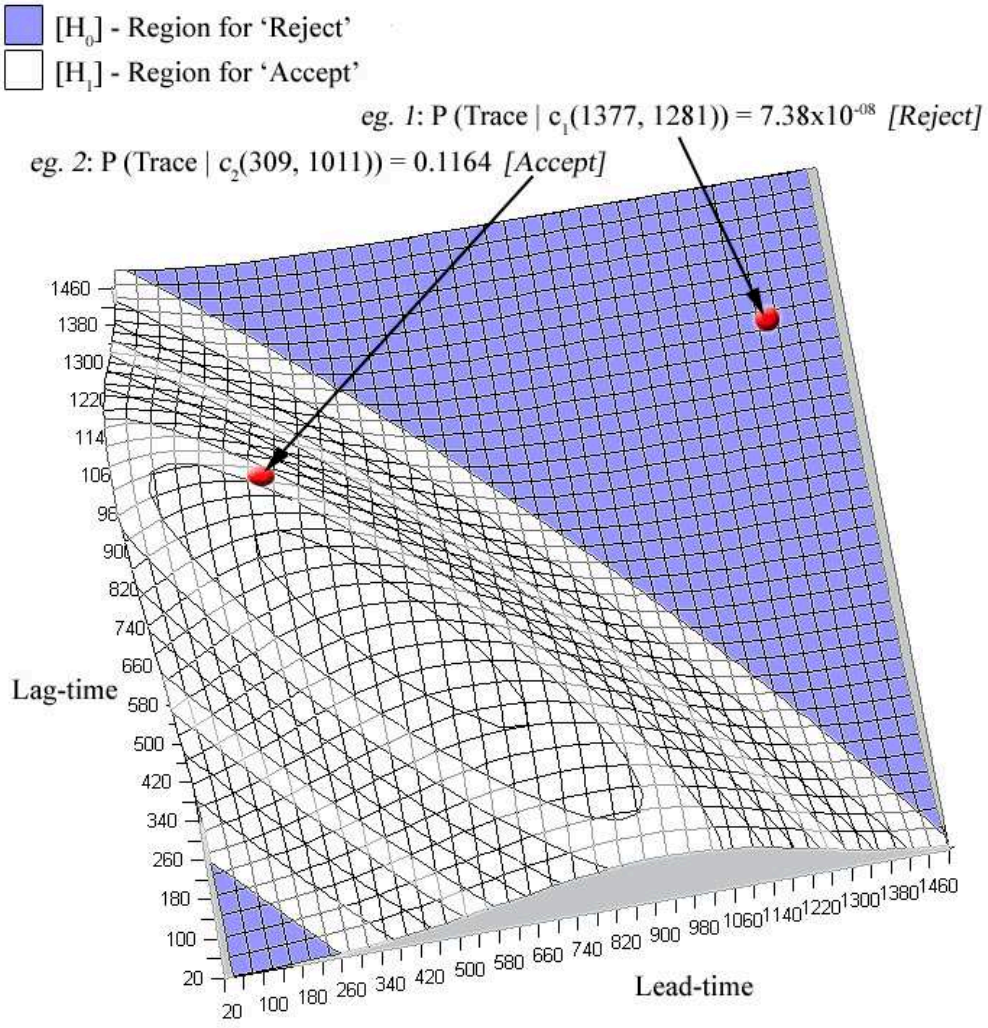

Figure 9: Incorporating the normal bivariate density to assist with the null and alternative hypotheses.

7.3 Small Chances of Getting a Command Gesture

We mentioned in Section 2.3 that the probability of occurrence of stand-alone ink components is very small. We also made the assumption that all command Gestures be categorised collectively as stand-alones to fit our timing definitions. Our preliminary analysis of the sample data indicates the findings shown in Table 2.

Total ink components sampled	9750	(100.00 %)
Stand-alone components (inclusive of command Gestures)	554	(5.79 %)
Command Gestures ONLY	118	(1.23 %)

Table 2: Breakdown of ink components with focus on stand-alones.

We iterate again that it is not very often that people choose to Gesture in the midst of writing sentences (or drawing pictures) on the board. They only Gesture to invoke commands to correct mistakes, access files, edit current writings, and browse between canvas screens. Table 2 proves this claim, as we see that command Gestures make up only 1.23% of all sampled ink components (which makes up 21.3% of all stand-alone components).

The hypotheses graph depicted in Figure 9 highlights areas for rejection that seem a little too large. However, based on the facts in Table 2 and of our dissection of the scatter-plot diagram in Figure 5, we believe that the lookup table obtained from the hypotheses graph is true and concise enough to make reliable decisions for all future ink components.

8 Works in Progress

Our investigation of the lead and lag times resulting from freehand writings on digital boards is part of the on-going process of managing, analysing, and reacting to all primitive ink data perceived from a writing environment. We currently have in place, a background process-model, designed to actively assist running foreground applications tailored for the Perceptual user Interface (PUI) paradigm [4, 5]. Part of this model is shown in Figure 10.

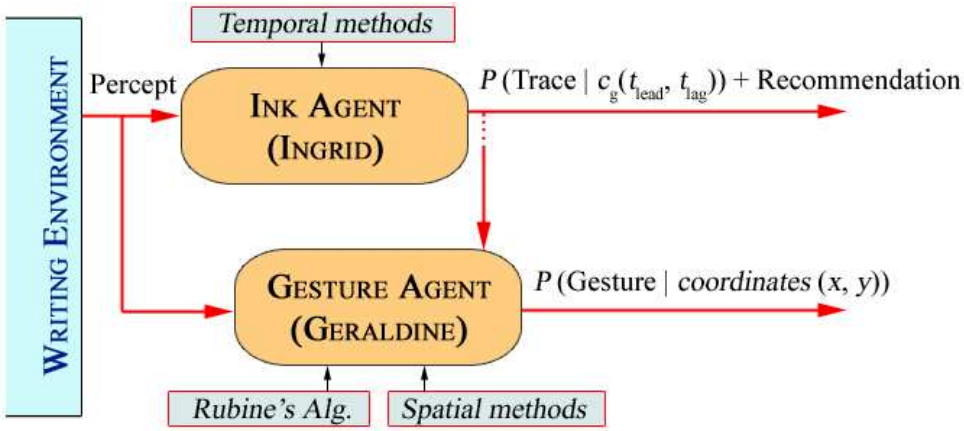

Figure 10: The PUI model's background Agency.

8.1 The Ink Agent Gateway

This report has shown that it is possible to place a lot of emphasis in the first stages of analysing incoming ink components. We believe that the temporal methods highlighted so far are statistically strong for influencing future decisions down the communication chains within the PUI model. Such that, by simply incorporating serious temporal analysis of all individual ink components, we can reduce the number of active parallel processes running in the background.

Previously, both Ingrid and Geraldine execute simultaneously at every instance of a new ink component, or whenever a change has occurred within the observable writing environment. Both agents run their own diagnostics – Ingrid building internal KD-trees, and Geraldine running Rubine's algorithm [7] after extracting the necessary features needed for its linear classifier. Only when both agents are satisfied with their own routines, can a third agent (Amidala) come into the picture to make a final verdict; deciding the entity of the ink component in question, and basing its hypothesis mainly on Geraldine's outputs.

Now however, we want to switch this emphasis to Ingrid, where we will allow only this agent to actively track the writing environment, but only when the user is superfluously writing. That is, we still require both agents to actively perceive their environment when there occur 'environmental' changes such as loading or reloading of ink data, and while affecting editorial amendments on multiple ink components.

For every ink component perceived, Ingrid will quickly consult her lookup probability table and then promptly return the value of P (Trace | c_g (t_{lead}, t_{lag})) together with her recommendation. Should this recommendation be the null hypothesis H_0, Ingrid then lets Geraldine know that the current ink component in question is not likely to be an instance of a symbolic Trace. This will trigger the mechanisms in Geraldine to begin its part of the overall collaborative routine in determining the chances for that ink component being a command Gesture.

8.2 Combining Temporal with Spatial Analysis

We plan to include additional spatial methods inside Geraldine for it to percept the complete environmental information, analyse its spatial contents (with respect to the current ink component), and return the value of P (Gesture | *coordinates* (x, y)). Gross [2] explain this technique in complete details, and the works by Calhoun et al. [1] included provisions for monitoring multi-stroke symbols.

As we expect to branch out from working with single-stroke Gestures to incorporating multi-stroke Gestures in our PUI model, it is essential that we observe the constituents of any affected ink components through their geometric properties. Most of the literature reviewed so far point towards the further segmentation of ink components into their primitive forms of lines and arcs for "symbol recognition" on a 2D surface. Others use predicates to represent spatial relations – an example of this high-level technique is shown in Figure 11.

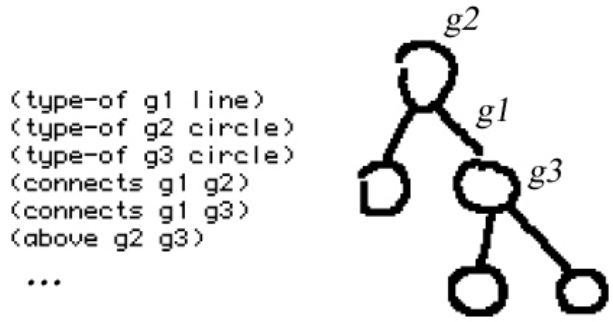

Figure 11: Predicate example of a "tree diagram".

The combined approaches of both Ingrid and Geraldine are expected to outline our 'anticipatory' concept of the background Agency through temporal and spatial techniques. While we wait for this proposal to achieve its accurate and strong evaluations when tackling the overlapping domains between Traces and Gestures, we can rest assure that our current mode of 'anticipation' is able to sustain precise decision-makings for ambiguous cases while still using very little processor time.

8.3 Managing and Manipulating Physical Graphical Objects

Our recently completed studies on the effects of gaming with Gestures [9, 10] suggest that graphical objects can be made for animations if physical properties like mass, friction, and vectored velocity are incorporated. The studies show that we can make these physical

graphical objects (PGO) respond to our command Gestures in a manner that is most natural. For if we gesture hard and fast on any selected PGO, it will move correspondingly towards the given direction quickly and smoothly – following the speed and style of input of our command Gesture. It will also push aside any other PGOs in its path due to the correct interpretation (and execution) of its physical properties.

We intend to run experiments in treating each individual ink component (in our present context) as instances of physical graphical objects. We will however ensure, that our earlier definitions of ink Traces, ink components, and command Gestures will still stand. The only difference will be the way the data structures are managed and manipulated while in memory to suit the additional new physical properties.

Moving freehand shapes on the digital board will be our next goal. And because each of those shapes would already have a unique spatial relationship to its neighbouring freehand shapes as described in Section 8.2 (if one exists), then manipulating that shape in corresponding relation to its neighbours will essentially require additional heuristics (or algorithms) to ensure a proper and correct transitional animation.

For example, a leaf that is part of a binary tree, when asked to swap with another branch, must guarantee the correctness of the swapping algorithm, its affected internal data structures of the ink components involved, and the visual Traces seen on screen. This problem need to be formulated appropriately, and aptly solved through our current structures and models.

9 Conclusion

We have investigated the lead and lag times of digital freehand writings and drawings, and found that there exist a direct correlation of the lead-lag times (categorised as *beginnings*, *endings*, *in-betweens*, and *stand-alones*) and the probability of the ink component being a symbolic Trace. Our final lookup probability table, which is the resultant joint distribution of the lead and lag times through the normal bivariate density function, gives very reliable outcomes of accepting or rejecting the chances of ink components as symbolic Traces. These results are incorporated into our Ink Agent and are expected to boost the overall performance of our current PUI model.

In future, we can expect other forms of improvements to ensure a solid program structure when working in all domains of the digital ink.

Acknowledgement

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