# Understanding Map Operations in Location-based Surveys

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***Abstract*—Location-based surveys have been moving to handheld computing devices as the availability of such devices has become more common. The more limited screen size of the handheld devices has made the maps more difficult to use. The present work looks at the map operations of users to determine if they are having problems. Two studies have been analyzed to get an understanding of the types of patterns that might be used to identify users that are having trouble. The choice of the two studies was to find two studies that were quite different and use one of the studies to find patterns of map operations that would indicate that a user was having problems. The second study could then be used to test the relevance of the patterns in a different implementation of the same task. We have identified patterns of interest using the data from the first study and found that the same patterns were relevant in the second study.**

***Keywords—location-based surveys, map operations.***

## I. INTRODUCTION

As computing devices have become common place, we are seeing more location-based surveys use handheld devices in the field. On many of these handheld devices screen space continues to be limited. As a result, maps in these surveys can be difficult to work with.

The present work focuses on understanding the types of difficulties that field staff have with map operations (e.g., zoom and pan) in such survey instruments. Ultimately, we are interested in whether it is feasible to identify map operation patterns that suggest that a map user is in trouble. To look at this question, we have evaluated the results of two studies that use the same survey task (address verification), but different implementations.

We couldn't find existing research results that directly apply to this problem. The closest work looked at map errors in the context of the sequence of map operations that were used to create a new map. Examples are Lodwick et al. [3] and Haining et al. [2]. More recently, work on map operations have used previous users' work to inform other users. For example, Wong et al. [7] looked at the impact of seeing previous users' map operation footprint in crowd

Shneiderman [6] looks at the notion of the Visual Information Seeking Mantra. The concept is related to the work discussed here in that Shneiderman's approach provides a framework for designing geographic software applications.

Roth [4] provides an overview of map-based primitives that provide the underpinnings of the map operations used in our studies.

The main contribution of this paper is that we were able to identify patterns in the data from Study 1 that suggested that the user was in trouble when he/she was using the map operations (zoom and pan) and verify that the same patterns could be used in the second study in spite of the differences in the way that the software was implemented. We also looked at the different treatments used in the two studies to extent this result over multiple variations of the software implementations. The fact that the two studies used different devices and were conducted in very different environments enhances the second study as a means of validating the patterns. Our tests show that the patterns could be found early enough in sequences of map operations that intervention has the potential to result in significant savings in terms of the number of map operations the user ultimately performed.

The remainder of the paper is divided as follows: Section II briefly reviews the two user studies used in the analysis. The results are presented in Section III. Section IV provides a discussion of the results. Finally, we look at conclusions and future work in Section V.

## II. METHODS

### *A. Overview*

The experimental task (address verification) involves comparing a housing unit configuration on the ground with the corresponding information in the map. Possible outcomes are: *1)* the ground situation is correctly reflected in the map requiring no further action; *2)* the map has an error of commission that requires a map spot to be removed; *3)* the map has an error of omission that requires a map spot to be inserted; and *4)* the map has an error in the housing unit location that requires the map spot to be relocated.

The term *scenario* is used to indicate the process of completing the verification of one address. The scenario

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type was not significant as one would expect since the bulk of the map operations are used to get to the point that the user is able to view the addresses on the map in the target area.

The next two sub-sections briefly overview the relevant details of the two studies. The maps are based on the US Bureau of Census's Tigerline maps. The *map spots* on the maps are used as identifiers of the location of housing units. For example, the spot labeled 507 in Fig. 2 indicates the current map location of the target address – 507 Astaire Ct.

Beyond having the same survey task the implementations used in the two studies are different. Even within the two studies there are different treatments to be considered.

Figure 1: The computer set up used in the Study 1.

## B. Study 1

Thirty-five participants were recruited from the community to perform 10 address verification scenarios. The map used in the software instrument covered a city of slightly over 40,000.

The experiment was designed to impose a rigid protocol on the participants. To successfully perform the task for each address, the following steps need to be executed in sequence: 1) find the address on the ground (i.e., in the photos presented to the subject ), 2) locate the address on the software map, 3) answer a question posed by the software as to whether or not the address was on the map, 4) if so, answer a question posed by the software as to whether or not the address was in the correct location on the map, and 5) fix the map if an error was identified.

To focus the participants on the software instrument, the participants were seated at a table with two monitors showing the two sides of the street (Fig. 1). The application recorded the time it took participants to perform each step in the procedure, the number of attempts to match each address, the number of attempts to fix the map, the accuracy in fixing the map, and the number of times specific buttons or other software tools were used.

Two treatments were used in the experiment – guided (17 participants) and unguided (18 participants). The screen shown in Fig. 2 illustrates the guided treatment. The guided statements were general statements to indicate the next step in the protocol.

In addition to the rigid protocol another important property of Study 1 is that the map was reset after each completion of a scenario.

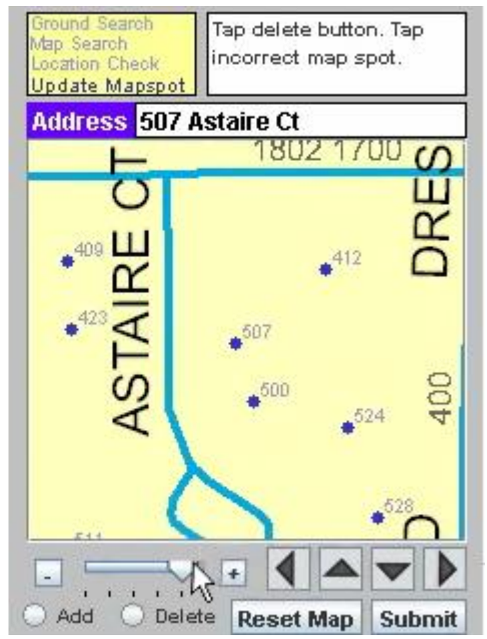


Figure 2. The guided interfaces of Study 1.

A more detailed look at the original user study can be found in Rusch, et al. [5].

## C. Study 2

Thirty-one participants performed the address verification task for 6 addresses in the second study.
The second study required to physically navigate the address space. The map of the address space covered a 3X4 block neighborhood of Ames, Iowa. The participants in the study were divided into two treatments (field and virtual reality (VR)). The field group went into an Ames, Iowa neighborhood and had to navigate as well as perform the address verification on the software. The VR group performed the same task, with the exception that the navigation took place within Iowa State University's C6 (a fully immersive virtual reality environment).

A key difference between the two studies is that in Study 2, the participants could choose the scenario they wanted to work on in any order. They could also revisit any scenario at any point in their work. Fig. 3 shows a screen shot of the software showing the scenario menu. Another important difference is that completing a scenario in Study 2 did not automatically reset the map. Rather the map view remained the same until the participant performed another map operation.

A more detailed look at the original user study can be found in Batinov, et al. [1].

## IV. RESULTS

### A. Overview

Each operation performed by a participant in both studies was logged and time stamped. To look at the map operations, the log files have been parsed to generate the string of map operations. Examples of the parsed results for the two studies are given in Figs. 5 and 6, respectively. The legend for the map operations common to both studies is given in Fig. 4.

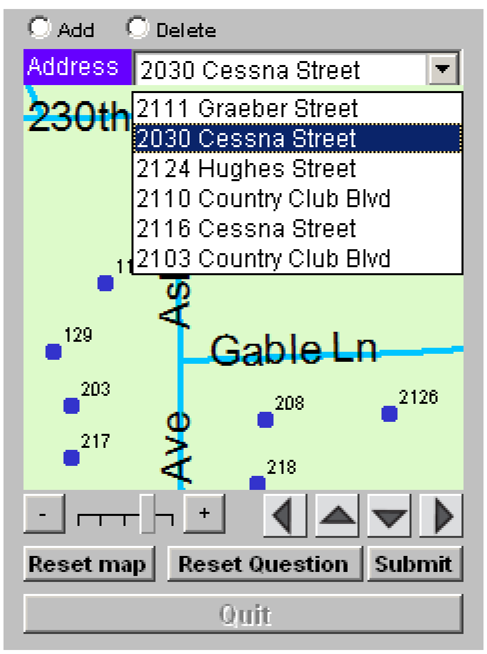


Figure 3. Edit screen with address list extended.

Before looking at the results of our investigation, we need to introduce some terminology that is important to the remainder of the paper. A *count pattern*, denoted n(list of unique map operations) is detected if the map operations in the list appears n times in the scenario sequence. For example, the count pattern 3(A) means that we are looking for the appearance of 3 up pans (A) that appear in the sequence. Note they do not have to be consecutive operations. Looking at line two in Fig. 5, we see that the line contains the count pattern 3(A). Note that it also contains 1(A), 2(A) and 4(A).

A *reversal count pattern* is a count pattern where the map operations in the list represent a reversal. For example, n(+-), n(AV) and n(<>) are reversal count patterns. Since they are only counts, n(AV)=n(VA) for each of the reversals.

The next sub-section looks at results for the first study.

\+ - zoom in by clicking + icon
B - one level zoom in using the scroll bar
C - two level zoom in using the scroll bar
b - one level zoom out using the scroll bar
c - two level zoom out using the scroll bar
\- - zoom out by clicking – icon
x - center zoom click
> - pan right
< - pan left
A - pan up
V - pan down
R - reset map
* - attempted to pan beyond the map borders

Figure 4. Map operation symbols common to the two data sets.

### B. Study 1 Results

Fig. 5 shows the map operations for one of the 35 participants. Each line in the data represents the map operations for one scenario.

```
+x>+xV-R>++><>
+x+xV>-+xA>VAAVV+AVR++><<<VV<<--+>R<>+<+x
<+>VVV-R+xAAVVVVVVAAA+A
+<<R+xVAAAAAR<<<<<>>>>+xA+xA><>
+x+x><-+>-+x>><<-+xVV
+xV+x-+VA
+x+xAA>V<R+x+x>
+xV+xVA
+x+x
+x+x-+VA
```

Figure 5. Sample map operation data showing one line for each scenario for Study 1.

One obvious type of count pattern that tends to generate extraneous operations is a reversal. Table I shows the number of scenarios (out of 170) that contained at least two or three (n=2 and n=3) reversal count patterns for the guided treatment. Table II provides similar results for count patterns for the individual pan operations with n=2 and n=3.

TABLE I. Number of scenarios in the guided data set that contain the reversal count patterns.

| Reversals | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(z+)n(z-) | 19 | 0.112 | 10 | 0.059 |
| n(>)n(<) | 36 | 0.212 | 20 | 0.118 |
| n(A) n(V) | 55 | 0.324 | 36 | 0.212 |

TABLE II. Number of scenarios in the guided data set that contain pan count patterns of n= 2 and n=3.

| Pan Count Patterns | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(>) | 52 | 0.306 | 30 | 0.176 |
| n(<) | 52 | 0.306 | 31 | 0.182 |
| n(A) | 72 | 0.424 | 45 | 0.265 |
| n(V) | 65 | 0.382 | 49 | 0.288 |

Table III shows the number of map operations that participants used after one of the reversal count patterns was encountered at either the n=2 or n=3 levels in the guided treatment. Table IV shows the same results for the pan operators.

TABLE III. Number of the 17 participants in the guided data set that used the reversal count patterns.

| Reversals | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(z+)n(z-) | 13 | 0.765 | 9 | 0.529 |
| n(>)n(<) | 15 | 0.882 | 9 | 0.529 |
| n(A) n(V) | 17 | 1.000 | 13 | 0.765 |

TABLE IV. Number of the 17 participants in the guided data set that contain pan count patterns of n= 2 and n=3.

| Pan Count Patterns | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(>) | 17 | 1.000 | 13 | 0.765 |
| n(<) | 15 | 0.882 | 13 | 0.765 |
| n(A) | 17 | 1.000 | 14 | 0.824 |
| n(V) | 17 | 1.000 | 15 | 0.882 |

Table V shows the number of map operations that participants used after one of the pan or reversal count patterns were encountered at either n=2 or n=3 levels. The second value is the number of scenarios that contain one or more of the count patterns.

TABLE V. Number of map operations/impacted scenarios after encountering a reversal or a pan count pattern of size n in the guided data set.

| n | pans | reversals | both |
|---|---|---|---|
| 2 | 1130/104 | 815/72 | 1194/108 |
| 3 | 886/75 | 578/46 | 911/78 |

Tables VI-X show the same results for the unguided treatment (180 scenarios). Table XI shows the same results for the full data set (35 participants) after the optimal set of map operations have been removed from each scenario. The optimal set of map operations was determined by examining each scenario.

TABLE VI. Number of scenarios in the unguided data set that contain the reversal count patterns.

| Reversals | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(z+)n(z-) | 33 | 0.183 | 19 | 0.106 |
| n(>)n(<) | 53 | 0.294 | 33 | 0.183 |
| n(A) n(V) | 58 | 0.322 | 44 | 0.244 |

TABLE VII. Number of scenarios in the unguided data set that contain pan count patterns of n= 2 and n=3.

| Pan Count Patterns | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(>) | 66 | 0.367 | 45 | 0.250 |
| n(<) | 70 | 0.389 | 48 | 0.267 |
| n(A) | 82 | 0.456 | 56 | 0.311 |
| n(V) | 68 | 0.378 | 51 | 0.283 |

TABLE VIII. Number of the 18 participants in the unguided data set that used the reversal count patterns.

| Reversals | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(z+)n(z-) | 13 | 0.722 | 10 | 0.556 |
| n(>)n(<) | 16 | 0.889 | 12 | 0.667 |
| n(A) n(V) | 16 | 0.889 | 14 | 0.778 |

TABLE IX. Number of the 18 participants in the unguided data set that contain pan count patterns of n= 2 and n=3.

| Pan Count Patterns | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(>) | 17 | 0.994 | 17 | 0.994 |
| n(<) | 17 | 0.994 | 14 | 0.778 |
| n(A) | 16 | 0.889 | 14 | 0.778 |
| n(V) | 17 | 0.994 | 16 | 0.889 |

TABLE X. Number of map operations/impacted scenarios after encountering reversals or a pan count pattern of size n in the unguided data set.

| n | pans | reversals | both |
|---|---|---|---|
| 2 | 1537/111 | 1167/84 | 1568/112 |
| 3 | 1239/82 | 863/59 | 1261/84 |

### *C. Study 2*

Fig. 6 shows the map operations for one of the 31 participants in Study 2. The map operations use the same symbols as were shown in Fig. 4. The other new symbols JZ, KZ, LZ, MZ, NZ and PZ indicate the selection of one of the six scenarios used in this study. As can be seen from Fig. 6, participants can open and work on a scenario at any time.

TABLE XI. Number of map operations/impacted scenarios after the optimal set of map operations have been removed.

| n | pans | reversals | both |
|---|---|---|---|
| 2 | 2560/199 | 1838/151 | 2634/205 |
| 3 | 2034/148 | 1352/101 | 2072/153 |

JZ--A<V><AVV><>Ax<br>
PZ<V<AAVV>cBxBV<V<>AA><><BV><<>V<><br>
MZ<br>
PZ<br>
MZV<>V<>A<<VA>b>--++>>><<-+V**<br>
NZ<>><<<<>>><A<<V>>>>*<><A<<V+-<br>
KZ>>><<><>><<<A<br>
NZ<>>-->-++-++--++<V---<br>
LZxA<<>>V<br>
NZ<<A<br>
LZ<>-->>AA<<VVxAVA<br>
JZ>V>>V

Figure 6. Map operations showing one line for each open scenario for Study 2 for one participant.

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From Fig. 6, it is clear that the notion of a scenario is not as consistent as it was in Study 1. Moreover, since it is not clear that operations at the end of a line are consistent with the open scenario, combining map operations from multiple lines for the same scenario is not meaningful. As a result, we use each line as a representation of a unit task. Table XII shows the number of lines containing reversal and

Table XII. Line counts for reversal and pan count patterns for n=2 and n=3.

| Operations | Count n=2 | Average n=2 | Count n=3 | Average n=3 |
|---|---|---|---|---|
| n(z+)n(z-) | 59 | 0.2063 | 40 | 0.1399 |
| n(>)n(<) | 93 | 0.3252 | 63 | 0.2203 |
| n(A) n(V) | 53 | 0.1853 | 28 | 0.0979 |
| n(>) | 116 | 0.4056 | 74 | 0.2587 |
| n(<) | 116 | 0.4056 | 83 | 0.2902 |
| n(A) | 62 | 0.2168 | 36 | 0.1259 |
| n(V) | 72 | 0.2517 | 45 | 0.1573 |

pan count patterns for the full Study 2 dataset (both VR and field). Tables XIII-XV show the number of the number of map operations that exist beyond the count patterns for the full Study 2 dataset, the VR treatment and the field treatment, respectively. The full dataset contains 286 lines of map operations, while the two treatments (VR and field) consist of 157 and 158 lines, respectively.

TABLE XIII. Number of map operations/impacted lines after encountering a reversal or a pan count pattern for the complete dataset and n= 2 and n=3.

| n | pans | reversals | both |
|---|---|---|---|
| 2 | 1607/153 | 1350/124 | 1703/164 |
| 3 | 1135/103 | 857/87 | 1242/113 |

TABLE XIV. Number of map operations/impacted lines after encountering a reversal or a pan count pattern for the VR treatment dataset and n= 2 and n=3.

| n | pans | reversals | both |
|---|---|---|---|
| 2 | 997/88 | 834/67 | 1039/91 |
| 3 | 730/58 | 559/51 | 782/62 |

TABLE XV. Number of map operations/impacted lines after encountering a reversal or a pan count pattern for the field treatment dataset and n= 2 and n=3.

| n | pans | reversals | both |
|---|---|---|---|
| 2 | 610/65 | 516/57 | 664/73 |
| 3 | 405/45 | 298/36 | 460/51 |

### *D. Comparing Results*

To compare the results from the two studies, we used the unpaired t-test with the null hypothesis that the two populations differ. The data drawn from the two studies for this test was the number of map operations that appeared after one of the count patterns was detected. Table XVI shows the values for the count patterns for n=2 and n=3. The value of p in both cases is not significant. As a result, we see the potential map operations saved from two very different implementations as being statistically equivalent.

Table XVI. T-test values comparing the potential savings from the two studies.

| Study 1 vs Study 2 | t | dff | p |
|---|---|---|---|
| n=2 | 1.5459 | 382 | 0.1230 |
| n=3 | 1.3928 | 273 | 0.1648 |

We found very similar results when we compared the treatments (guided vs unguided and field vs VR) using the same approach.

## V. DISCUSSION

The goal of this study was to use Study 1 to identify interesting count patterns and use the Study 2 data to see whether the same patterns are valid there as well. We have chosen to work with the raw data to provide a view of potential savings that intervening might bring to users of a survey instrument. Note that we are only looking at the potential savings, while realizing that the participant would still have to complete the task.

The expectation is that intervening would give them the opportunity to more efficiently complete the task. Pans in both studies have the side effect of causing some participants to wander. Also note that we are not looking to statistically compare results across studies or treatments. Rather we simply are looking to identify potential count patterns that exist in different implementations. The fact that the implementations of the software, the study environments, and the devices used are very different makes our approach of using the Study 2 data to validate our results more interesting.

### *A. Study 1*

The Study 1 data has been evaluated across the two treatments as well as the complete dataset. From Tables I, II, VI, and VII, we find that the reversal and pan count patterns show up in both treatments. Table V illustrates that for all of the scenarios that contain a count pattern at either n=2 or n=3, there are more than 10.8 map operations per impacted scenario that could potentially be saved for the guided treatment. From Table X we see that there are even more map operations after the count patterns for the unguided treatment (at least 13.2 map operations per scenario impacted). Recognizing the count patterns and intervening gives the potential to significantly reduce the user frustration in map based surveys. This is especially useful in the handheld environment, where small screen size tends to complicate the use of maps.

Tables III, IV, VIII, and IX look at the number of participants that incur at least one of the count patterns. Here we see that over half of the participants in the guided treatment (0.529) and unguided treatment (0.556) have used at least one count pattern. The number of participants for most count patterns is closer to 1.0. Table XI shows the same results for the complete Study 1 dataset after the optimal query has been removed from each scenario string. The idea behind this data was to only consider the extraneous map operations in each line of map operations. Again, we find that the average number of additional map operations in the line to be over 12.1 per scenario.

From these results, we believe that the reversal and pan count patterns for n=2 and n=3 are reasonable choices for determining that a user is having difficulties using the map operations. In the next subsection we look at the impact of these count patterns on the Study 2 dataset.

### B. Study 2

As noted earlier, the software implementation for Study 2 provided a more flexible protocol. Two important differences are that the participants could work on any scenario at any time and that the map was not reset at the completion of a scenario as it was in the first study. The first difference resulted in a breakdown in the way that scenario could be used. In the first study, a scenario was essentially the same as a line of data. In the second study a scenario was typically opened on more than one line. Since there is no way to relate operations on an open scenario to the scenario (the participant could be positioning the map for another scenario), the task unit was interpreted as a line of map operations.

The second difference is somewhat more important in the context of this study. Since the map was not reset after the completion of a scenario, most participants in the second study tended to use pans to move on to the next address location on the map. This provides an interesting point, as the optimal approach was to reset the map after completion of a scenario rather than use pans. A third difference is the size of the underlying map. The smaller map for Study 2 should mean less pans, but the pan count pattern numbers are still quite large. In addition to these three differences the two studies differed in the type of device used as well as the environment used for the study.

The result has been that we see the count patterns from Study 1 being useful in Study 2. Looking at Fig. 6, it is easy to see how this one participant tended to wander on the map when he/she was using pan operations. More important, the results in Tables XIII and XV show that the count patterns have been found early enough in the lines of map operations to potentially save participants from using extra pan operations and reversals.

## VI. CONCLUSION AND FUTURE WORK

We were able to find an interesting set of map operation count patterns based on pans and reversals in two different implementations of the address verification task. Our next step is to use the count patterns in a new user study where we can intervene and study the actual impact on participants. Ultimately, our goal is to use the map operation count patterns found in this work to provide an adaptive approach to help users struggling with using maps on the mobile devices that agencies like the Bureau of Census are starting to use in the field for large tasks like address verification.

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