Optimizing a Personalized Multigram Cellphone Keypad

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Abstract

Current layouts for alphabetic input on mobile phone keypads are very inefficient. We propose a genetic algorithm (GA) to find a suitable keypad layout for each user, based on their personal text history. It incorporates codes for frequent multigrams, which may be directly input. This greatly reduces the average number of strokes required for typing.

We optimize for two-handed use, the left thumb covering the leftmost rows and vice versa. The GA minimizes the number of strokes, consecutive use of the same key, and consecutive use of the same hand. Using these criteria, the algorithm re-arranges the 26 alphabetic characters, plus 14 additional multigrams, on the 10-key pad. We demonstrate that this arrangement can generate a more effective layout, especially for SMS-style messages. Substantial savings are verified by both computational analysis and human evaluation.
1 INTRODUCTION

Current cell-phone keypad layouts are of two kinds: unambiguous and ambiguous. Unambiguous layouts have enough keys to uniquely map the intended alphabet to the keys – the QWERTY keyboard is an example. This is straightforward to learn, but difficult to use because keys are too small for finger use due to the lack of space on mobile phones.

Thus ambiguous layouts, with fewer keys than alphabetic characters, are widely used. Two mechanisms are used to resolve the ambiguity as to which letter is intended: multi-tap and contextual disambiguation. Multi-tap uses repetition: letters on the same key are distinguished by number of strokes. The most widely-used 12-key layout falls into this category. Although easy to learn due to the natural ordering, it is inefficient to use – most obviously because of the high average number of key strokes. In addition, it performs poorly for single-thumb text entry because of the high average distance the thumbs must move. But most important, a 12-key pad only permits us to type one character per key press. Since English (like most languages) has many common digrams and trigrams, a pure unigram encoding misses important opportunities for efficiency.

The other alternative is disambiguation algorithms. In these, the user types only a single stroke per letter, regardless of the position of the intended letter on the key. The disambiguation algorithm guesses the intended word using statistical characteristics of the language. For example, when the user types key sequence ‘63’, the algorithm guesses the intended word as ‘of’, based on the frequency of English words. If the user does not intend ‘of’, the algorithm shows the next most probable word, ‘me’. However predictive methods are not a panacea. Nesbat argues that disambiguation methods create unreasonable cognitive loads: the user has to continually check whether the intended word has been recognized, and edit it if not. The problem is even worse when the intended words are not in the dictionary. The user must change to direct input mode and re-type. This case, however, is surprisingly frequent, especially in SMS. Because of the restricted message length, users often contract words to abbreviations: ‘btw’ for ‘by the way’, for example. They also commonly use proper names for people or places. Nesbat also notes that users frequently mix languages, as in ‘Hello Amigo’; thus predictive methods based on standard dictionaries perform unexpectedly poorly.

We aim to overcome these limitations by supporting personalization and multigrams. Optimization based on a personal SMS archive has many merits. Most important, a personalized layout is efficient. Ideas for remapping keypad layouts to date have assumed a standardized layout, and used a standard frequency table. However, letter and bigram frequency differs user by user, culture by culture, despite use of the same language. To be specific, American, British, and Australian usages differ in word frequency, spelling, and SMS practice, although all use English. Reflecting and taking advantage of these differences can increase speed. For instance, ‘q’ is more frequently used in Canada, because of its French culture. A personally-optimized layout may allow this generally-rare letter to be on a better position. Personalization allows us to take advantage of each user’s frequent words or phrases – even those containing foreign languages (e.g. amigo), proper nouns (e.g. SNU, LG), abbreviation (e.g. btw, 4u), slang (e.g. wusup), and even emoticons (e.g. :) ). A personalized character input system has further potential. It may support assistive technology by reflecting a specific user’s difficulty in typing. A personalized layout can also work as a security tool by recognizing the owner’s usual pattern of use.

Another key idea in this paper is multigrams. Frequently-used bigrams or trigrams are used in the layout, inputting more than one letter at once. Note that the list of multigrams is also personalized: frequently-used ones in the individual archive are selected. In a sense, selecting multigrams can be seen as a prediction algorithm (multigram, instead of word). We believe that selecting personally-frequent multigrams improves prediction accuracy compared to a standard word prediction system. In the latter, the user must check whether the intended word is chosen and edit it if not. In a multigram layout, this risk is low once the user sufficiently memorizes his own layout.

We constrain this work to English 12-key layout, although the method can be readily extended to other single-byte character systems like Spanish. Only 10 keys are used for typing, with two keys reserved for special purposes, such as input of special characters and mode change. Upper and lower case in the user archive is ignored because case is distinguished generally by mode, not by key. We also assume availability of memory to record the user’s keystroke history.

In the rest of the paper, we provide the historical context relating to keyboard layout optimization and personalization first, followed by a detailed description of our methods. Then, we detail the evaluation design and results, using a computational analysis, following this with a human evaluation. Lastly, we conclude with a summary of the contribution, limitation and our planned future work.
2 BACKGROUND

2.1 Optimizing Mobile Keypads

Many researchers have tried to optimize mobile keyboards. We can classify their work firstly by the kind of physical keypad. For ambiguous keypads, MacKenzie and Zhang [9] designed a soft keyboard OPTI, redesigning the keyboard shape and key distribution. Zhai et al. [13] also designed a virtual keyboard for touch screens, optimizing with the Metropolis algorithm. They measured the efficiency of several existing virtual keypads including QWERTY. Despite this work, unambiguous keypads are little used in mobile phones, probably due to space limitations for keys.

By contrast, multi-tap and disambiguation are widely used in cell-phones. For predictive systems, Lesher et al. [7] optimized the character-level disambiguation rate for a given text, using the n-opt algorithm (well-known from Traveling Salesman Problems – TSP). The keystrokes per character (KSPC) dropped to 1.09. Gong and Tarasewich [4] added another constraint: assigning characters in alphabetical order. They observed KSPCs ranging from 1.05 (written article) to 1.25 (text messages on mobile phone), for 10 keys. This resulted from a disambiguation rate of up to 98.13% for written text and 95.13% for SMS.

Genetic Algorithms (GA) have often been used to optimize layouts. How and Kan [5] remapped key layout with a simple GA. They also tried to improve accuracy of word prediction by investigating previous words in addition to the current key sequence.

GAs have also been used for remapping keys for multi-tap layouts. Moradi and Nickabadi [10] use a GA to optimize, based on a frequency sample. For a given sample, their GA minimized average strokes, delay due to consecutive use of the same key, and moving distance to type the given sample, with an assumption that only one thumb is used for typing. In their metric, typing cost dropped from 2.90 (current layout) to 2.25 (optimized). They stated that the theoretical minimum of the cost function is 1.70. We note that these cost values depend heavily on characteristics of the text, including the variety of words, the kinds of words, and the occurrence of special characters. We use their work as a basis for comparison with our new, multigram approach.

2.2 Personalized Keyboards

All these methods implicitly assume that keyboard design should be standardized. Nguyen et al. [12] argue that universal keyboards are unnecessary due to the rise of standard interfaces, such as USB, W-USB, and Bluetooth. For both computer and mobile phone input, personalized key layouts can be readily downloaded into such devices. They propose a GA to generate a user-optimal key layout for 10-finger pure-chording devices.

2.3 Genetic Algorithms

GAs are powerful methods for tough search spaces, performing well on most problems, and being relatively easy to use. We refer readers to a standard text such as De Jong’s [3] for a detailed background. They may be divided into two classes, generational (at each stage, the parent population generates a new, separate population constituting the next generation), and steady-state (individual parents produce children, which then compete with parents to replace them).

We use GAs in two places: choosing multigrams for the layout, and choosing the arrangement of keys. We use steady-state GAs, in which one (mutation) or two (crossover) parents are chosen randomly from the current population. The relevant operator is applied, producing a child, which competes deterministically (truncation selection) with the parent(s), the least fit being eliminated from the population.

3 MOTIVATION

3.1 Criteria for Keypad Optimization

We assume that both thumbs are used for typing. This is the fastest mode for SMS input from a keypad, and thus automatically focuses on those users most interested in speed, and most likely to adopt a new input mode. Thus unlike Moradi and Nickabadi’s [10], our fitness function emphasizes the number of key strokes rather than distance (because distances for two-thumb operation are generally small).

In this context, three criteria determine the efficiency of a layout. Most important, fewer key strokes per character improve input speed. We need between one and three strokes to type a character in current systems. For example, we use three strokes to type “F” but only one for “G”. If frequent characters use the first-stroke position, we would reduce the overall number of strokes. But frequent characters vary from person to person, so reflecting the personal history is important in minimizing the number of strokes.
Second, if we want to type another letter using the same key, we must include a delay or type an additional stroke to move the cursor – either slows typing. Thus reducing the probability of consecutive use of the same key, based on the personal archive, will improve typing efficiency. Moradi also uses this criterion, with a slightly different weight factor.

Finally, for two-thumb use, alternating thumbs eliminates thumb movement from consideration: the alternate thumb can move into position while the first makes a stroke. Thus our penalty should only apply when the same thumb must be used for consecutive letters.

We need to combine these three criteria, weighting them to reflect their impact on typing speed. A more formal description is given below. We also incorporate multigrams in the layout. While these improve typing efficiency, they do not introduce any further complications to the fitness function.

### 3.2 Formal Description

Using these criteria, we define a three-part fitness function:

\[ f_1 = \frac{\sum l \text{st}(l)}{C} \]

where \( \text{st}(l) \) is the number of strokes required to type character \( l \), and \( C \) is the total number of characters in the corpus.

\[ f_2 = \frac{\sum l \text{sk}(l)}{C} \]

where \( \text{sk}(l) \) is 1 if consecutive characters use the same key, else 0. In the text "What is this?", if 't' and 'h' are located on one key and 'i' and 's' on another, the numerator of equation 2 would be 3, because t-h, i-s, and the second i-s share the same key. Thus equation 2 gives a penalty of 0.3.

\[ f_3 = \frac{\sum l \text{sh}(l)}{C} \]

where \( \text{sh}(l) \) is 1 if consecutive characters use the same hand, 0 otherwise. Thus the penalty for LLRLRLR is 1, and 3 for RLLLRRL. However, there is a complication. We assume that keys on the left column use the left hand, and vice versa. But the middle column may be typed with either hand – whichever was not used last. We can define the parity of a sequence of middle column characters as follows: when we have two non-center characters using the same hand, separated by an even number of middle-row characters, or else opposite hands separated by an odd number, we say they have even parity, otherwise odd. When the parity is even (i.e. the character stream cannot be typed with alternating hands), the penalty is 1, otherwise it is 0. Of course, this assumes foresight of arbitrary length on the part of the typist. In general, long sequences of central characters will be rare, so the effect of limited foresight will be small.

The overall adaptive fitness function is defined as:

\[ F_A = \alpha f_1 + \beta f_2 + \gamma f_3 \]

Normalizing by setting \( \alpha = 1 \), we can rationally choose relative values for the other terms. \( f_2 \) penalizes repeated use of the same key. Speed-conscious typists will use the cursor key rather than a timeout, so the cost is one stroke; but the cursor key is located inconveniently (compared to other keys), so we set \( \beta = 1.5 \). For \( f_3 \), the effect of same-hand use is relatively minor, so we use \( \gamma = 0.25 \).

In comparisons with Moradi and Nickabadi, we use their distance term

\[ f_4 = \frac{\sum l \text{d}(l, \text{prev}(l))}{C} \]

with \( \text{d}(a, b) \) defined as \( \sqrt{(r_a - r_b)^2 + (c_a - c_b)^2} \), with \( r \) and \( c \) denoting row and column. Their cost function is then:

\[ F_M = \alpha_M f_1 + \beta_M f_2 + \gamma_M f_4 \]

where \( \alpha_M = 0.7, \beta_M = 3 \) and \( \gamma_M = 1 \) as in [10].

### 3.3 Multigrams

To further improve typing speed (and reduce \( f_1 \)), we introduce multigrams in our coding, and assign key positions for frequently-used multigrams. Thus one key stroke may create more than one character. In this paper, we allow at most four strokes for each key. Using ten keys, this gives 40 available slots. Because there are 26 letters in the English-Roman alphabet, 14 slots are available for multigrams. Thus we first choose the best combination of the 26 letters and 14 multigrams to minimize the overall cost function.
It might seem that we could simply select the 14 most frequent multigrams. However two key issues preclude this. First, the most frequent bigrams may overlap the most frequent trigrams. For many corpora, “er” and “ert” will be frequent. However if we include “ert” in our coding, other occurrences of “er” may be too rare to justify a separate coding. Second, multigrams will change the unigram frequencies of their constituent letters. For example, if “of” occurs 30 times, “o” occurs 100 times, and “f” occurs 50 times, then a multigram for “of” covers 30% of “o” and 60% of “f”. This reduction in the frequencies of “o” and “f” may result in their assignment to low key positions (requiring more key strokes), freeing up their otherwise-higher positions for other keys which are now more frequent.

Instead of selecting the 14 most-frequent multigrams, we assume the relevant ones will be among the 50 commonest bigrams and trigrams of the archive. To select the 14 multigrams in the coding, we pre-process with an initial GA. Our variant of GA uses an eager initialization: the 14 multigrams are selected by roulette sampling based on their frequency of occurrence (i.e. the probability of selection is proportional to the frequency), where a typical GA would use uniform sampling. It also uses eager operators. The crossover operator preserves all multigrams that occur in both parents, then selects other multigrams from either parent in order of frequency (a more typical crossover would randomly select the multigrams from either parent). The mutation operator randomly, but at a low rate (1%) replaces the 14 multigrams with others from outside the top 50 (in order to improve the solution when our initial assumption was wrong). For the fitness function, we use the sum of the changes in rank of the unigrams, since this tells us how often the multigrams will be located on high-priority key positions, and hence serves as a proxy for the key strokes they will save. We use deterministic selection between a child and its parent(s). We run the GA for 1000 repetitions, with a population of 50, which seems to be sufficient to give convergence to an optimum.

Once we have determined the 14 multigrams, we treat them exactly like ordinary letters, letting them compete for fewer strokes and better positions. If the frequency of a multigram is low, it may be allocated a bad position such as 4 strokes. If this results in more strokes than direct input would require, the multigram is deprecated.

## 4 THE CORE GENETIC ALGORITHM

The search for the best arrangement of the alphabet (including the chosen multigrams) on the keypad is not easy. This is a rough search space with many local minima, and with difficult-to-satisfy constraints. Straightforward optimization algorithms will fail, repeatedly generating infeasible solutions. We use a steady-state GA to find a good arrangement.

A GA can be described by specifying five components – the genotype representation, the initialization process, and the crossover, mutation and selection operators – together with a number of parameters detailing the exact set-up.

### 4.1 Chromosome Expression

Our chromosome has the following structure:

```java
public class Solution {
    private Gene[40] gene;
    private int size;
    private int id;
}
```

```java
public class Gene {
    private int row;
    private int column;
    private int stroke;
}
```

Thus there are 40 genes, one for each letter. Each gene gives the assigned location for the corresponding letter (row, column, strokes). Corresponding to the 4 rows and 3 columns of the keypad, row has the range 1 to 4, and column 1 to 3. The strokes value specifies the number of strokes to type the character, also 1 to 4. Table 1 shows a typical chromosome.

|   | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | .. | 39 |
|---|---|---|---|---|---|---|---|---|---|---|----|----|
| R| 2 | 1 | 3 | 3 | 1 | 2 | 2 | 1 | 4 | .. | 4  |    |
| C| 3 | 2 | 2 | 3 | 1 | 2 | 2 | 1 | 1 | 2 | .. | 2  |
| S| 4 | 1 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | .. | 3  |

Table 1: Example Chromosome
There are two restrictions. Because we use only 10 of the 12 keys excluding key ‘∗’ and ‘#’, two locations (4,1) and (4,3) should not occur. So genes such as (4, 1, 1) and (4, 3, 3) are forbidden. Also, each gene represents a unique location and number of strokes, so no duplicates are allowed: every gene should be unique. Crossover and mutation must maintain these properties.

4.2 Initialization
Each individual in the initial population is a permutation of the letters on the keypad, the permutations being sampled uniformly randomly.

4.3 Crossover
In crossover, we aim to create children lying semantically between parents. We define between formally as: a gene $g_1$ is between genes $g_2$ and $g_3$ if each component (row, column, strokes) lies in the closed interval defined by the corresponding values in $g_2$ and $g_3$. A chromosome is between two others if all corresponding genes satisfy this property. In the early stages of evolution, each element may have a large range, but we expect it to converge to a specific value because of the influence of fitness on selection.

To help construct children lying (if possible) between parents, we use two data structures: a 3-dimensional array $[4, 3, 4]$ of lists candidate, expressing the possible keypad structures; and a 1-dimensional array of 40 integers possibleCount, containing the number of between positions where the corresponding gene can be placed. For each gene we determine the possible locations that lie between the corresponding genes of the parent. For example, if the parents for gene $x$ are (1, 2, 3) and (3, 2, 4), the candidate locations are (1, 2, 3), (1, 2, 4), (2, 2, 3), (2, 2, 4), (3, 2, 3), and (3, 2, 4). We insert $x$ in every corresponding position in the list array candidate, while gene $x$ in possibleCount gets the value 6 (for the six possible locations). This process is repeated for every gene. Thus candidate array contains every possible gene that can be placed at each location, while possibleCount contains the number of possible locations for each gene.

Then the arranging algorithm first searches for genes with possibleCount 1. This occurs when both parents have identical (row, column, stroke) values. Thus the child has only one possible position for this gene; it is automatically located there. Thus no other gene can occupy the same position: their possibleCount is reduced by 1.

When all remaining genes have more than one choice, the algorithm moves on to a gene with only two choices (we call this value, 2, the level). Of its two candidate positions, we choose the one with fewest remaining possible genes. Thus if one position has 6 possibilities and the other 2, we choose the latter – again, eliminating this choice from other genes. The aim is to leave open as many choices as possible for the remaining genes. Note that this process may move some other gene to level 1 (by eliminating one of its two choices). Thus at each stage, the algorithm should re-start from level 1, and always choose a gene from the lowest available level. Since this process always increases levels, and since the levels cannot exceed the number of available places, it must terminate in at most $40 + 39 + 38 + \ldots + 1 = 820$ iterations.

There is one exception. In rare cases, we may not be able to satisfy the between condition - the possibleCount may drop to zero. One option, in this case, is to backtrack and try alternatives. However this is expensive. Since GAs need a source of randomness anyway (and indeed, mutation is included just for this purpose), we adopt a simple solution: when a gene cannot be located between its parents, we allocate it randomly among the vacant positions, and adjust the data structures correspondingly. In fact, this is rarely used (less than one case in 100).

4.4 Mutation
We used a number of mutation operators: swapping two columns (24 to 28), swapping two rows (24), swapping two keys (8), reorganizing strokes in a key(4), and exchanging a pair of letters(2). (The figure in parenthesis means corresponding number of genes affected by the mutation.) Thus the first two may be viewed as relatively global mutations, exploring the search space, while the last three are local mutations, searching the space finely.

4.5 Selection
For crossover, selection works by randomly selecting two parents, creating the child, then holding a tournament between the parents and the child, with the loser dropping out of the population. Parents for mutation are chosen randomly, with the child always replacing the parent.
5 COMPUTATIONAL ANALYSIS

To compare the typing cost of Personalized Multigram (PM) and ABC layouts, we used a computational analysis followed by human evaluation. Here, we measure the theoretical improvement by comparing fitness values.

5.1 Experimental Design

| Type | Words | Letters | Description |
|------|-------|---------|-------------|
| SMS  | 554   | 2766    | Recent SMS messages by the first author |
| FCB  | 725   | 3358    | Instant messages gathered from Facebook |
| ART  | 378   | 2340    | An article relating to a social issue [1] |

Table 2: Profile of Archives used in Experiments

The number of characters include empty space.

To test effectiveness, we used three kinds of text (Table 2). Each archive came from one author, reflecting our aim of matching personal use. The first uses recent Short Message Service (SMS) messages of the first author. The second uses Facebook (FCB) postings, based on an assumption that language usage may be similar in SMS and social networks – in terms of topics (personal issues dominate), frequently occurring abbreviations and emoticons. The last is an article (ART) from TIME magazine [1], which should reflect general usage, but also include characteristics of the author in word choice, voice, and use of pronouns; but the article does not contain the abbreviations and emoticons typical of SMS. All characters are either one of the 26 English letters, or special characters normally found on phone keypads.

5.1.1 Parameter Settings

GAs are stochastic; runs may give different results. In comparisons, we need to run multiple trials, assessing differences statistically; we used 50 trials for each treatment. It is also essential to use fair comparisons. Results can be improved by extra computation so it is important to compare equal effort. This is usually specified as the number of potential solutions evaluated (in our case, keyboard configurations). Parameter Settings are shown in Table 3.

| Parameter                  | Value |
|----------------------------|-------|
| Number of Trials           | 50    |
| Population size            | 50    |
| Number of Evaluations      | 50,050|
| Mutation rate (each of 5 types) | 0.01  |
| Crossover rate             | 1     |
| Algorithm type             | steady-state |
| Selection                  | Parent-child tournament |
| Elite Size                 | 1     |

Table 3: Experimental Parameters

5.1.2 System Environment

We conducted these experiments on an Intel Core 2 @ 2.13GHz machine with 2GB RAM. MS Windows XP Professional SP 3 was used for OS, and our analysis program ran under Java 2 Runtime Environment, Standard Edition 1.4.1.
| Text | Multigram Pad | Random Keypad | Optimized Keypad |
|------|---------------|---------------|------------------|
|      | Best          | Average       | Best             | Average         |
| SMS  | With 2.14     | 2.07          | 2.14 ± 0.03      | 2.07 ± 0.02     |
|      | W/O 2.37      | 2.40          | 2.54 ± 0.04      | 2.01            |
| FCB  | With 2.41     | 2.40          | 2.50 ± 0.04      | 2.04 ± 0.01     |
|      | W/O 2.37      | 2.40          | 2.54 ± 0.04      | 2.01 ± 0.01     |
| ART  | With 2.12     | 2.12          | 2.24 ± 0.04      | 1.77 ± 0.02     |
|      | W/O 2.66      | 2.53          | 2.65 ± 0.05      | 2.07 ± 2.01     |

Table 4: Comparison with Moradi, using Moradi Metric

|          | Moradi’s Cost Function | Two-thumb Cost Function |
|----------|------------------------|-------------------------|
|          | SMS  | FCB   | ART   | SMS  | FCB   | ART   |
| W        | 3775 | 3775  | 3775  | 3761 | 3755  | 3726  |
| E(W)     | 2525 | 2525  | 2525  | 2525 | 2525  | 2525  |
| σ(W)     | 145.1| 145.1 | 145.1 | 145  | 145.1 | 145.1 |
| Z_w      | 8.62 | 8.62  | 8.62  | 8.52 | 8.48  | 8.28  |
| P        | < 10^{-15} | < 10^{-15}               |

Table 5: Wilcoxon Rank Sum Test on Multigrams

For multigrams, all samples from keypads with multigrams have lower cost than those without, so W has the maximum possible value, 3775.

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5.2 Result and Analysis

5.2.1 Comparison with Moradi and Nickabadi

We first compare our approach with Moradi and Nickabadi. Table 4 compares five layouts using Moradi’s cost function: ABC, random (with/without multigrams), and optimized (with/without multigrams), on the three archives in Table 5. Optimized layouts with multigrams always perform best, both in best found and average. The ABC layout has similar (slightly worse) efficiency than random layouts. Optimized layouts show better efficiency in every setting, just as Moradi suggests. Efficiency is further improved by multigrams, in both random and optimized layouts. These results are generally consistent with those of Moradi and Nickabadi (standard layout 2.90, optimized layout 2.25), based on part of “Harry Potter 5: The order of the Phoenix.” The exact value depends on the text, but in general, optimization based on Moradi’s metric is effective in reducing typing costs for a mobile phone keypad.

Moradi also mentions that 1.70 is the theoretical optimal value. However this theoretical value is based on a single character per position/strokes combination. In Table 4 we can see that multigram keypads can approach and even exceed this theoretical optimum (in SMS). A restriction to single-character prevents \( f_1 \) and \( f_2 \) being less than 1. With multigrams, our design allows up to 3 characters per stroke, so \( f_1 \) can be below 1. \( f_2 \) can also be less than 1, because multigram use can eliminate thumb movements required to type the characters within the multigram. For example, assume that we type the word “this.” Without multigrams, we have to pay at least 2 points for this string. If some characters are on the same key, the delay penalty is 3, larger than a 1 point move.) So, the minimum cost of thumb movement is 4. With multigrams “th” and “is,” however, we need only two movements, so the minimum thumb movement cost is 2. Thus \( f_4 \) for this string is 0.5 (movement cost 2 divided by length of the string 4). In sum, our tests show that the multigram design can exceed the theoretical optimal value of 1.70 suggested by Moradi.

To statistically confirm the effectiveness of multigrams for optimizing a keypad, we provide a comparison using the Wilcoxon rank sum test (Mann-Whitney U test), with \( n = n = 50 \). By the central limit theorem, the sample approximates a normal distribution. Table 5 summarizes the test, listing sample size \( n \), rank sum for without-multigram case \( W \), its mean \( E(W) \) and standard deviation \( \sigma(W) \), its normalized value \( Z_w \), and its significance level \( P(Z > Z_w) \). Each column tests the hypothesis that use of multigrams makes no difference to the efficiency of that keypad. From the normalized \( Z_w \) values, the probabilities that these results arise are all less than 10^{-15}.

5.2.2 Optimization for Two-Thumb Typing

Moradi’s function assumes we use only one thumb, so the average movement distance is important. With two thumbs, minimizing consecutive use of the same hand is more important. We also use different weight factors.
We can see from Table 6 that the current ABC keypad has much the lowest efficiency – far worse than random layouts. The optimization algorithm demonstrates its effectiveness, through the improvement from random to optimized layouts. Multigrams further improve the efficiency, for all texts. Again, all results are significant below the $10^{-15}$ level.

5.2.3 Influence of Text Archive

For both fitness functions, the algorithm found better fitness values for SMS than for FCB or ART. In most cases, SMS is significantly better than FCB, and FCB is slightly better than ART. Thus the algorithm is especially relevant to text such as SMS on mobile phones – the form of text that dominates use of these keypads. Specifically, the hypothesis that use of words and patterns in language are more highly personalized in SMS appears correct. Improvement is also seen in FCB and ART, but the magnitude is lower. Gong and Tarasewicz [4] also make such a comparison, but their design shows lower efficiency on SMS than on written or spoken language. In this respect, our algorithm is far more effective for SMS on mobile phones.

5.2.4 Detailed Analysis of Keypad Examples

Table 7 details our best layout for each archive. Introducing multigrams improves every aspect affecting fitness. The average number of strokes is reduced by 16.5% (SMS), 7.4% (FCB), and 6.7% (ART). For SMS, we average 1.01 strokes per character – approximately one character per stroke, despite the ambiguous layout. Gong [4] suggests the minimum number of strokes per character is 1.05 for written and spoken language and 1.25 for SMS, for 10 keys. Our layout substantially improves this – 1.01 for SMS and 1.12 for written language (ART). Figure 1 shows the corresponding layouts.

In SMS, “u” is located on a 4-stroke position, although it is a frequent letter in English, because the layout covers most uses with multigrams (“ou” and “you”). In FCB, six multigrams are deprecated, but non-letters on the layout significantly improve efficiency. For example, “33” may be used for common emoticons like “:<333333.” This layout also contains another emoticon “=)”. Special characters and case shifts generally require mode changes, so directly supporting these phrases in the layout significantly improves efficiency. In ART, we find “the” and “ing” – the commonest trigrams in general English – because ART reflects general characteristics of English.

Table 6: Comparison Using Two-Thumb Metric

| Text | Multigram | ABC Pad | Random Keypad | Optimized Keypad |
|------|-----------|---------|---------------|------------------|
|      | With      | Best    | Average       | Best             | Average         |
| SMS  | W/O       | -1.41   | 1.57 ± 0.05   | 1.06             | 1.19 ± 0.04     |
| FCB  | W/O       | -1.54   | 1.63 ± 0.03   | 1.23             | 1.27 ± 0.01     |
| ART  | W/O       | -1.58   | 1.71 ± 0.04   | 1.19             | 1.24 ± 0.01     |

Light-colored multigrams are deprecated, as they do not improve typing speed compared to use of single characters.
### Table 7: Fitness Details of Best Solutions

|     | Multi-gram Fitness | Mean Strokes | Same Key | Same Hand |
|-----|---------------------|--------------|----------|-----------|
| SMS | W/O 1.06284         | 1.01880      | 0.00614  | 0.13846   |
|     | W/O 1.34275         | 1.21908      | 0.05531  | 0.16269   |
| FCB | W/O 1.23325         | 1.13513      | 0.03661  | 0.16076   |
|     | W/O 1.35152         | 1.22774      | 0.05567  | 0.16106   |
| ART | W/O 1.19618         | 1.12586      | 0.01751  | 0.17214   |
|     | W/O 1.30019         | 1.20973      | 0.04118  | 0.17471   |

6 USER STUDY

Although this personalized-multigram (PM) layout seems efficient, we need to verify its speed in real use, and test its acceptability in ease of use, learnability, and memorability, compared with the ABC-layout.

6.1 Evaluation Design

6.1.1 Procedure

The overall idea is to compare typing speed between PM and ABC by measuring elapsed time for each participant typing sample messages displayed on the screen. We used the same device (Figure 2 left) and same program UI (Figure 2 right) for testing both layouts. Only the keypad layout shown on the bottom was different. The programs for the two layouts were compiled separately, yielding two different executables.

To observe the after-training speed and verify learnability, we repeat the experiment for several sessions. A session consists of a set of 5 English text messages of 15 to 30 bytes. Each participant is instructed to repeat at least 10 times, but they are free to do more until they feel no further improvement is possible for each layout. In order to simulate casual use of text messages, the experiment is spread over 2 to 3 days for each participant. Participants are guided to try any time they wish during the test period. After the completion of the sessions, a questionnaire is distributed to check their satisfaction level and subjective feeling of improvement. Messages are randomly selected from a pool of real SMS texts, because this experiment aims to evaluate a mobile phone layout. A few examples:

- have a nice day :-)
- omg.. take more than a month..
- heyhey i got a msg from her!!

The program interface is shown in Figure 2. After entering name and pressing the START button, it displays a message to type. For each message, it records typed text and time in milliseconds, from the first letter press to the OK button (on the keypad). For accurate measuring, we instructed subjects not to pause during a message. Using the records, we measure the subject’s typing speed and accuracy as the average typing time per character, imposing a penalty of 1 second per typo (calculated as the Levenshtein Distance between target and answer). For the unfamiliar PM layout, the key arrangement is shown on the screen.\(^3\)

\(^3\)There is some cognitive load in this, imposing a slight bias against the proposed layout; in light of the results, this bias was not serious.
Table 8: Individual results in human evaluation

Typing speeds are in CPM (Character per minute), and PM means Personalized-Multigram. Speed Up denotes the percent speedup between PM-layout and ABC-layout typing speed. Cross-point denotes the first PM session at which the subject exceeded their ABC-layout speed.

| No. | Typing Speed (CPM) | Speed Up | Cross-point | Session Count | Age |
|-----|--------------------|----------|-------------|---------------|-----|
|     | ABC | PM First | PM Final |               |     |
| 1   | 36.47 | 22.60 | 76.87 | 111% | 3 | 14 | 26 |
| 2   | 35.01 | 28.65 | 74.65 | 113% | 3 | 17 | 33 |
| 3   | 55.20 | 49.42 | 104.50 | 89% | 4 | 22 | 27 |
| 4   | 65.21 | 29.64 | 82.91 | 27% | 3 | 12 | 26 |
| 5   | 30.43 | 20.40 | 37.79 | 31% | 3 | 7 | 28 |
| 6   | 72.84 | 50.09 | 100.30 | 38% | 7 | 23 | 25 |
| 7   | 37.26 | 22.66 | 46.43 | 25% | 6 | 9 | 24 |
| 8   | 56.52 | 14.28 | 43.13 | 24% | 19 | 34 | 61 |
| 9   | 33.37 | 19.13 | 50.26 | 51% | 17 | 22 | 53 |
| 10  | 46.49 | 32.40 | 71.73 | 54% | 4 | 20 | 25 |
| Avg | 44.88 | 28.93 | 69.26 | 54% | 6.90 | 18.00 | 32.8 |
| SD  | 14.69 | 12.27 | 23.43 | 35% | 6.03 | 7.97 | 13.1 |

6.1.2 Subjects

We tested 10 subjects, 9 male and 1 female. Most were researchers in computer science except for two. Seven were in their mid-20s, the other three being 33, 53, and 61. Average age was 32.8. Eight were Korean, the other two being from Australia and Spain.

This experiment required multiple trials over about 3 days for each participant, so it took a lot of time. In order to reduce the elapsed time, we shared the phone between people who used the same workspace all day. A university laboratory was chosen for this reason, although it led to some bias in gender and occupation. However, we strictly controlled experience and familiarity with the current mobile phone keypad, the most important factor for this experiment.

Note that our participants include two seniors, who showed dramatically slower improvement. For homogeneity of results, we excluded them from the analysis, as we show raw data in Table 8. It seems clear that age is a confounding variable that needs to be explored in more detail in future.

6.1.3 Apparatus

We used a Samsung Electronics SCH-M470 (Figure 2) because of its combination of a 12-key standard alphanumeric physical keypad with programmable smart-phone capabilities, making easy to install and run our test program. (Most other smart-phones use a touch-screen input method, which is inappropriate for this experiment.) The operating system is Microsoft Windows Mobile Version 6.0 Professional. The phone size is 101.5 x 53 x 16.8 mm. The program was developed in C++, using Microsoft Visual Studio 2008.

6.2 Results and Analysis

6.2.1 Result

Figure 3 shows an increasing trend in typing speed for both layouts. Each point is the average of all subjects’ typing speed at that session. At first, ABC speed (38.39 CPM) exceeds PM (32.22) – probably due to previous familiarity. By session 4, PM (47.41) speed overtakes ABC (44.72). Eventually, PM reaches 71.21 while ABC stagnates around 54. Over 14 sessions, subjects showed 121% improvement with PM, but only 42% with ABC. Individually, this ranged from 86% to 240% for PM, from 5% to 59% for ABC. Subjects show better performance with PM after only a few sessions, confirming PM’s efficiency.

In Table 8 we saw that the typing cost for SMS reduced from 1.90 (current layout) to 1.06 (optimized Multigram layout) – around a 44.2% improvement. Results from the human evaluation suggest that this is in the right ballpark. Specifically, subjects in the experiment averaged around 52.9% reduction in typing time, ranging from 14.3% to 80.8%.

6.2.2 Usability Issues

Usability is an important issue. A user familiar with ABC layout may not be prepared to make the effort required for another; a new user may prefer a layout that appears familiar (like ABC). In order to gauge this effect, we
distributed a questionnaire to each subject after completing all sessions. Each question used a six-point Likert Scale format: marking any point between 0 and 5.

We investigated usability by asking users’ personal feelings about both personalized layout and multigrams. We asked which is preferable between the personalized (5 point) vs. standardized layout (0 point). Average response was 3.25: the personalized pad was slightly preferable, but similar. For multigrams users showed greater satisfaction. Between perfectly satisfied (5 point) and not satisfied (0 point), the average response was 4.05. The final question asked users to choose between two options, personalized-multigram layout and current ABC-layout, assuming that no other layouts were available. We gave three options: PM-layout, ABC-layout, and ‘do not matter’. Six subjects out of 10 chose PM-layout, two ABC-layout and two ‘does not matter’. To sum up, we can conclude that subjects tended toward satisfaction with the personalized-multigram layout, in spite of its complete unfamiliarity.

Usability can be metricized for both learnability and memorability. We infer that the PM-layout is fairly easy to learn by investigating the overtaking point (first time that PM shows better performance). On average, each subject exceeded their own ABC speed in 4.7 sessions, ranging from 3 to 7. Early sessions take about 5 minutes, so they were able to learn PM layout sufficiently in about 30 minutes. We also asked about this in the questionnaire: “do you think you have improved in remembering each key’s location in the new layout, compared to the early stages of the experiment?” (very much - 5 point to not improved at all - 0 point.) For this question, almost everyone responded that they have improved, indicated by the average of 4.00. We conclude that PM layout is sufficiently easy to learn.

7 DISCUSSION

7.1 Contributions

The personalized multigram layout promotes much higher typing speed on mobile phones through two key features: an efficient arrangement of letters reflecting individual needs, and introduction of frequently-used multigrams. If the system were offered by manufacturers as a table-driven alternative, then users could generate the layout from a sample of their text, and upload it to any phone offering the feature. Of course, users would always have the option to use a table giving them the current (ABC) layout.

Some have voiced concern that phone keypads are being replaced by touch screens, vitiating this work. This may not reflect a truly international mindset. It is true that smart-phone use in the first world is rapidly increasing. According to market researcher In-Stat [6], the number of smart-phone users world-wide in 2009 was estimated at about 25 million, expected to increase four-fold by 2013. However, the total number of mobile phone users was about 3.1 billion in 2007, expected to increase to 4.5 billion in 2012. Thus keypad-based phones are still increasing in number, and will continue to increase over the immediate future; a tailorable keypad layout will continue to have value for a substantial time, and could offer market advantage to manufacturers. Equally important, the general philosophy of personalized layouts, optimized to a specific user’s pattern of use, is even more readily applicable to touch-screen smartphones than to keypad phones: the key entry is already purely software-based, so a tailorable system is easy to deploy.
7.2 Limitations

Although the personalized multigram layout has merit, it suffers from some limitations. Firstly, for a fixed layout, it has been the practice to engrave the letters on their corresponding keys. For a personalized layout, this is not so easy. It will generally be necessary to display the layout on the screen, at least while the user is learning it. This may restrict the use of screen space for applications. In typical phones, perhaps one third of the screen would be occupied by the layout, leaving only two thirds for applications. It might be possible to reduce this disadvantage through stick-on labels or other means, but it needs to be acknowledged.

Second, there is a small possibility that some hardware might need re-design to support this function, because the layout would need to be stored in memory. We suspect that current keypad phones actually do this anyway, to support easy customization to different alphabets in different markets. But this design information is not readily available from manufacturers, so we have been unable to confirm it.

Third, language usage patterns may change over time. In our proposed use model, the layout is fixed once it has been created, so it may become out-of-date, not reflecting the user’s pattern as well as it once did. Of course it is possible for users to re-run the algorithm at any time with a new sample of their text, and generate a new layout. However the new layout would impose a substantial challenge – re-learning. We address this further below.

Fourth, because of the high effort involved in testing, the user study we conducted, like all such studies in the literature, used a very small sample size (10) – too small for reliable statistical testing. However even ignoring the very small sample size, and treating the data as Gaussian, yields a confidence interval at the 5% level that includes zero: even at a 5% confidence level, and making very optimistic assumptions, we cannot exclude the possibility that there is no difference between PM and ABC layout speed. We suspect that this study is not alone in this respect, and that few such learning-based studies in the literature could withstand a detailed significance analysis.

Last (and least important), it takes some time to compute a new layout. In our computer system, it took about 3 to 5 minutes. If run directly on a mobile phone, it would take more time. Even in this case, it is required only infrequently, and could be run overnight during sleep.

7.3 Further Work

Changing patterns of use may change the optimal layout. But complete re-optimization is likely to generate very different layouts, imposing high learning loads on the user. Alternatively, the amount of change from the previous layout could be incorporated in the fitness function, to minimize the cognitive load while maintaining high typing speed. In general, the issue of how to maintain high typing speed in the face of changing use patterns, while also minimizing cognitive load, is a challenging research topic (not only for mobile phone keypads), worthy of a substantial research investment.

We would like to extend our experiments to a larger number of people with more varied backgrounds. Our current testing is somewhat limited in the sense of statistical stability. A large proportion of our subjects are young, male CS-majored graduate students. It appears likely, both from experience and from our experiments, that age is a strong determinant of learning. We need to test with more people with a wider range of characteristics, but the current protocol imposes a substantial effort on subjects, and over a long time. To overcome this, we have designed a new experimental protocol. We will be running detailed human experiments with a larger and more varied pool of subjects in the near future.

8 CONCLUSION

In this paper, we described an optimization algorithm for personalized mobile phone key layout using a multi-gram approach. Genetic algorithms are used to find both the best combination of multigrams, and the best key arrangement. The fitness function takes into account the average number of strokes required to type text, consecutive strokes on the same key, and consecutive use of the same hand. Applying this algorithm, we have found highly efficient multigram layouts for three kinds of archives: instant messages as used in cell phones; those used in social network services; and general articles. Fitness values for these best layouts are significantly smaller than for layouts without multigrams, and for unoptimized layouts – including the current alphabetically-ordered layout.

The general method is almost independent of language or character set – it can be applied to any single-level alphabetic language. With minor adaptations, it can handle multi-level alphabetic languages such as Korean, and unambiguous representations of ideographic languages (e.g. wu-bi method for Chinese), but not ambiguous representations (pinyin).

In comparison with previous work, we show that our design substantially improves efficiency. The advantage is particularly great for SMS texts. Human evaluation verifies its usability and learnability, and its impact on
performance.

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