Error-tolerant Finite-state Recognition with Applications to Morphological Analysis and Spelling Correction

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This paper presents the notion of error-tolerant recognition with finite-state recognizers along with results from some applications. Error-tolerant recognition enables the recognition of strings that deviate mildly from any string in the regular set recognized by the underlying finite-state recognizer. Such recognition has applications to error-tolerant morphological processing, spelling correction, and approximate string matching in information retrieval. After a description of the concepts and algorithms involved, we give examples from two applications: in the context of morphological analysis, error-tolerant recognition allows misspelled input word forms to be corrected and morphologically analyzed concurrently. We present an application of this to error-tolerant analysis of the agglutinative morphology of Turkish words. The algorithm can be applied to morphological analysis of any language whose morphology has been fully captured by a single (and possibly very large) finite-state transducer, regardless of the word formation processes and morphographemic phenomena involved. In the context of spelling correction, error-tolerant recognition can be used to enumerate candidate correct forms from a given misspelled string within a certain edit distance. Error-tolerant recognition can be applied to spelling correction for any language, if (a) it has a word list comprising all inflected forms, or (b) its morphology has been fully described by a finite-state transducer. We present experimental results for spelling correction for a number of languages. These results indicate that such recognition works very efficiently for candidate generation in spelling correction for many European languages (English, Dutch, French, German, and Italian, among others) with very large word lists of root and inflected forms (some containing well over 200,000 forms), generating all candidate solutions within 10 to 45 milliseconds (with an edit distance of 1) on a SPARCStation 10/41. For spelling correction in Turkish, error-tolerant recognition operating with a (circular) recognizer of Turkish words (with about 29,000 states and 119,000 transitions) can generate all candidate words in less than 20 milliseconds, with an edit distance of 1.

1. Introduction

Error-tolerant finite-state recognition enables the recognition of strings that deviate *mildly* from any string in the regular set recognized by the underlying finite-state recognizer. For example, suppose we have a recognizer for the regular set over $\{a, b\}$ described by the regular expression $(aba + bab)^*$, and we would like to recognize inputs that may be slightly corrupted, for example, *abaaaba* may be matched to *abaaba* (correcting for a spurious *a*), or *babbb* may be matched to *babbab* (correcting for a

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deletion), or *ababba* may be matched to either *abaaba* (correcting a *b* to an *a*) or to *ababab* (correcting the reversal of the last two symbols). Error-tolerant recognition can be used in many applications that are based on finite-state recognition, such as morphological analysis, spelling correction, or even tagging with finite-state models (Voutilainen and Tapanainen 1993; Roche and Schabes 1995). The approach presented in this paper uses the finite-state recognizer built to recognize the regular set, but relies on a very efficiently controlled recognition algorithm based on depth-first searching of the state graph of the recognizer. In morphological analysis, misspelled input word forms can be corrected and morphologically analyzed concurrently. In the context of spelling correction, error-tolerant recognition can universally be applied to the generation of candidate correct forms for any language, provided it has a word list comprising all inflected forms, or its morphology has been fully described by automata such as two-level finite-state transducers (Karttunen and Beesley 1992; Karttunen, Kaplan, and Zaenen 1992). The algorithm for error-tolerant recognition is very fast and applicable to languages that have productive compounding, or agglutination, or both, as word formation processes.

There have been a number of approaches to error-tolerant searching. Wu and Manber (1991) describe an algorithm for fast searching, allowing for errors. This algorithm (called **agrep**) relies on a very efficient pattern matching scheme whose steps can be implemented with arithmetic and logical operations. It is most efficient when the size of the pattern is limited to 32 to 64 symbols, though it allows for an arbitrary number of insertions, deletions, and substitutions. It is particularly suitable when the pattern is small and the sequence to be searched is large. Myers and Miller (1989) describe algorithms for approximate matching to regular expressions with arbitrary costs, but like the algorithm described in Wu and Manber, these are best suited to applications where the pattern or the regular expression is small and the sequence is large. Schneider, Lim, and Shoaff (1992) present a method for imperfect string recognition using fuzzy logic. Their method is for context-free grammars (hence, it can be applied to finite state recognition as well), but it relies on introducing new productions to allow for errors; this may increase the size of the grammar substantially.

2. Error-tolerant Finite-State Recognition

We can informally define error-tolerant recognition with a finite-state recognizer as the recognition of all strings in the regular set (accepted by the recognizer), and additional strings that can be obtained from any string in the set by a small number of unit editing operations.

The notion of error-tolerant recognition requires an error metric for measuring how much two strings deviate from each other. The **edit distance** between two strings measures the minimum number of unit editing operations of **insertion, deletion, replacement** of a symbol, and **transposition** of adjacent symbols (Damerau 1964) that are necessary to convert one string into another. Let $Z = z_1, z_2, \ldots, z_p$ denote a generic string of p symbols from an alphabet A. $Z[j]$ denotes the initial substring of any string Z up to and including the j^{th} symbol. We will use X (of length m) to denote the misspelled string, and Y (of length n) to denote the string that is a (possibly partial) candidate string. Given two strings X and Y, the edit distance $ed(X[m], Y[n])$ computed according to the recurrence below (Du and Chang 1992) gives the minimum number of unit editing operations required to convert one string to the other.

$$
\begin{aligned}
ed(X[i+1],Y[j+1]) &= ed(X[i],Y[j]) && \text{if } x_{i+1}=y_{j+1} \\
&&& \text{(last characters are the same)} \\
&= 1+\min\{ed(X[i-1],Y[j-1]), && \text{if both } x_i = y_{j+1} \\
&\qquad ed(X[i+1],Y[j]), && \text{and } x_{i+1}=y_j \\
&\qquad ed(X[i],Y[j+1])\} && \\
&&& \text{(last two characters are transposed)} \\
&= 1+\min\{ed(X[i],Y[j]), && \text{otherwise} \\
&\qquad ed(X[i+1],Y[j]), && \\
&\qquad ed(X[i],Y[j+1])\} && \\
ed(X[0],Y[j]) &= j && 0\le j\le n \\
ed(X[i],Y[0]) &= i && 0\le i\le m \\
ed(X[-1],Y[j]) &= ed(X[i],Y[-1]) = \max(m,n) && \text{(boundary definitions)}
\end{aligned}
$$

For example, $ed(recoginze, recognize) = 1$, since transposing i and n in the first string would give the second. Similarly, $ed(sailn, failing) = 3$ since one could change the initial s of the first string to f, insert an i before the n, and insert a g at the end to obtain the second string.

A (deterministic) finite-state recognizer, R, is described by a 5-tuple $R = (Q, A, \delta, q_0, F)$ with Q denoting the set of states, A denoting the input alphabet, $\delta : Q \times A \rightarrow Q$ denoting the state transition function, $q_0 \in Q$ denoting the initial state, and $F \subseteq Q$ denoting the final states (Hopcroft and Ullman 1979). Let $L \subseteq A^*$ be the regular language accepted by R. Given an edit distance error threshold $t > 0$, we define a string $X[m] \notin L$ to be recognized by R with an error at most t, if the set

$$C = \{Y[n] \mid Y[n] \in L \text{ and } ed(X[m], Y[n]) \le t\}$$

is not empty.

2.1 An Algorithm for Error-tolerant Recognition

Any finite-state recognizer can also be viewed as a directed graph with arcs labeled with symbols in A.[1] Standard finite-state recognition corresponds to traversing a path (possibly involving cycles) in the graph of the recognizer, starting from the start node, to one of the final nodes, so that the concatenation of the labels on the arcs along this path matches the input string. For error-tolerant recognition, one needs to find *all* paths from the start node to one of the final nodes, so that when the labels on the links along a path are concatenated, the resulting string is within a given edit distance threshold t, of the (erroneous) input string. With $t > 0$, the recognition procedure becomes a search on this graph, as shown in Figure 1.

Searching the graph of the recognizer has to be fast if error-tolerant recognition is to be of any practical use. This means that paths that can lead to no solutions must be pruned, to limit the search to a very small percentage of the search space. Thus, we need to make sure that any candidate string generated as the search is being performed does not deviate from certain initial substrings of the erroneous string by more than the allowed threshold. To detect such cases, we use the notion of a **cut-off**

1 We use *state* interchangably with *node*, and *transition* interchangeably with *arc*.

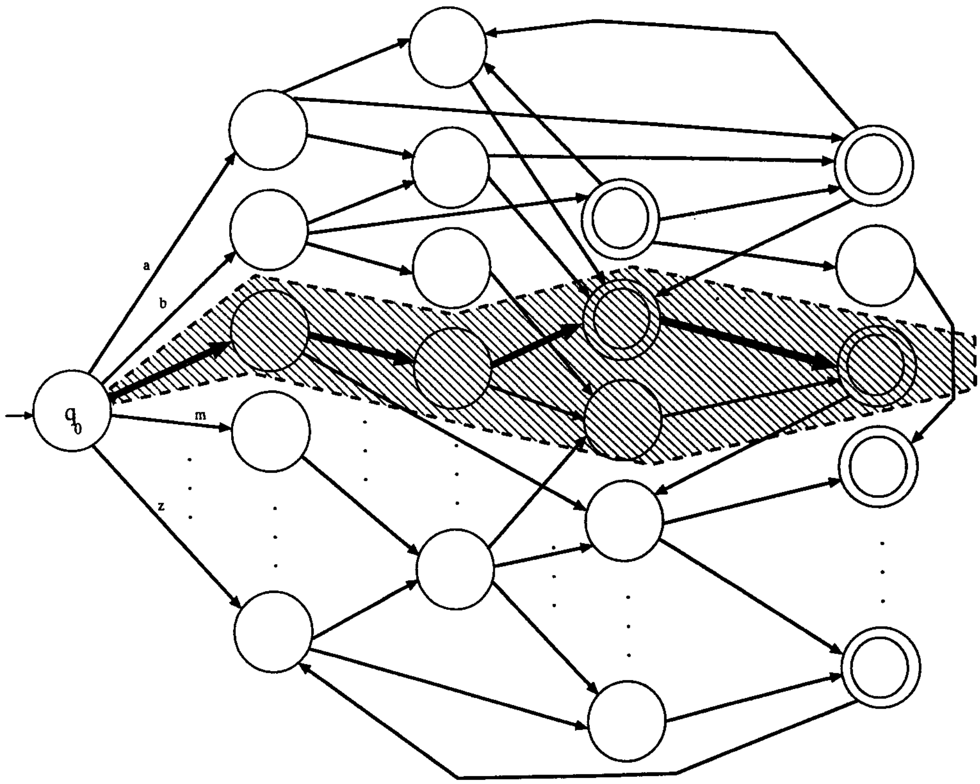


Figure 1
Searching the recognizer graph.

edit distance. The cut-off edit distance measures the minimum edit distance between an initial substring of the incorrect input string, and the (possibly partial) candidate correct string. Let Y be a partial candidate string whose length is n, and let X be the incorrect string of length m. Let $l = \max(1, n-t)$ and $u = \min(m, n+t)$. The cut-off edit distance $cuted(X[m], Y[n])$ is defined as

$$cuted(X[m], Y[n]) = \min_{l \leq i \leq u} ed(X[i], Y[n]).$$

For example, with $t = 2$:

$$\begin{aligned} cuted(\text{reprter}, \text{repo}) = \min\{ & ed(\text{re}, \text{repo}) = 2, \\ & ed(\text{rep}, \text{repo}) = 1, \\ & ed(\text{repr}, \text{repo}) = 1, \\ & ed(\text{reprt}, \text{repo}) = 2, \\ & ed(\text{reprte}, \text{repo}) = 3\} = 1. \end{aligned}$$

Note that, except at the boundaries, the initial substrings of the incorrect string X considered are of length $n-t$ to length $n+t$. Any initial substring of X shorter than

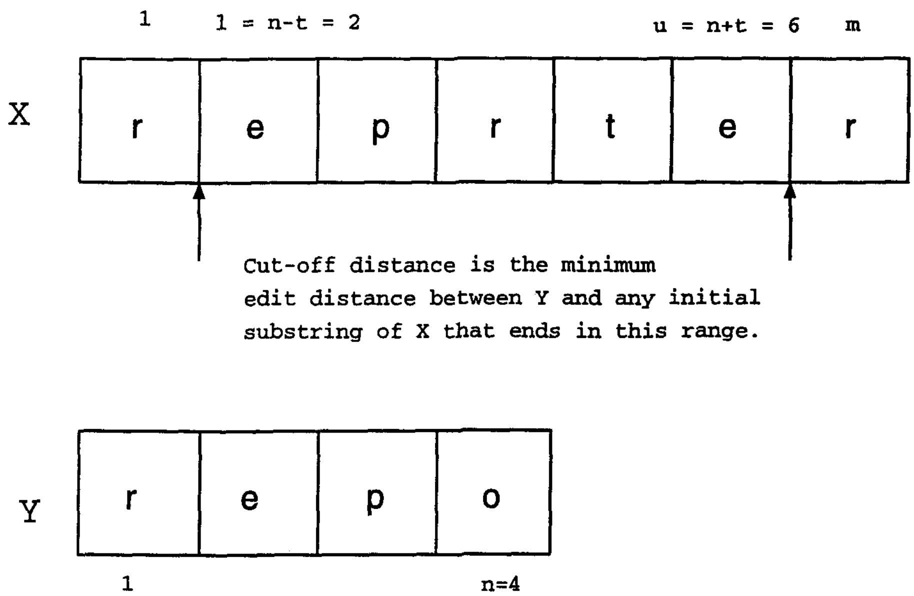


Figure 2
The cutoff edit distance.

$n - t$ needs more than t insertions, and any initial substring of X longer than $n + t$ requires more than t deletions, to at least equal Y in length, violating the edit distance constraint (see Figure 2).

Given an incorrect string X, a partial candidate string Y is generated by successively concatenating relevant labels along the arcs as transitions are made, starting with the start state. Whenever we extend Y, we check if the cut-off edit distance of X and the partial Y is within the bound specified by the threshold t. If the cut-off edit distance goes beyond the threshold, the last transition is backed off to the source node (in parallel with the shortening of Y) and some other transition is tried. Backtracking is recursively applied when the search cannot be continued from that state. If, during the construction of Y, a final state is reached without violating the cut-off edit distance constraint, *and* $ed(X[m], Y[n]) \leq t$ at that point, then Y is a valid correct form of the incorrect input string.[2]

Denoting the states by subscripted q's (q_0 being the initial state) and the symbols in the alphabet (and labels on the directed edges) by a, we present the algorithm for generating all Y's by a (slightly modified) depth-first probing of the graph in Figure 3. The crucial point in this algorithm is that the cut-off edit distance computation can be performed very efficiently by maintaining a matrix H, an m by n matrix with element $H(i,j) = ed(X[i], Y[j])$ (Du and Chang 1992). We can note that the computation of the element $H(i+1, j+1)$ recursively depends on only $H(i,j), H(i,j+1), H(i+1,j)$ and $H(i-1,j-1)$, from the earlier definition of edit distance (see Figure 4).

During the depth-first search of the state graph of the recognizer, entries in column n of the matrix H have to be (re)computed only when the candidate string is of

2 Note that this check is essential, since we may come to other irrelevant final states during the search.

```
/*push empty candidate, and start node to start search */
push((ε,q0))
while stack not empty
    begin
      pop((Y',qi)) /* pop partial surface string Y'
                       and the node */
      for all qj and a such that δ(qi,a) = qj
         begin /* extend the candidate string */
            Y = concat(Y',a) /* n is the current length of Y */
         /* check if Y has deviated too much, if not push */
            if cuted(X[m],Y[n]) ≤ t then push((Y,qj))
         /* also see if we are at a final state */
            if ed(X[m],Y[n]) ≤ t and qj ∈ F then output Y
         end
    end
```

Figure 3
Algorithm for error-tolerant recognition.

$$
\begin{pmatrix}
\cdots & \cdots & \cdots & \cdots & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
\cdots & H(i-1,j-1) & \cdots & \cdots & \cdots \\
\cdots & \cdots & H(i,j) & H(i,j+1) & \cdots \\
\cdots & \cdots & H(i+1,j) & H(i+1,j+1) & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
\cdots & \cdots & \cdots & \cdots & \cdots
\end{pmatrix}
$$

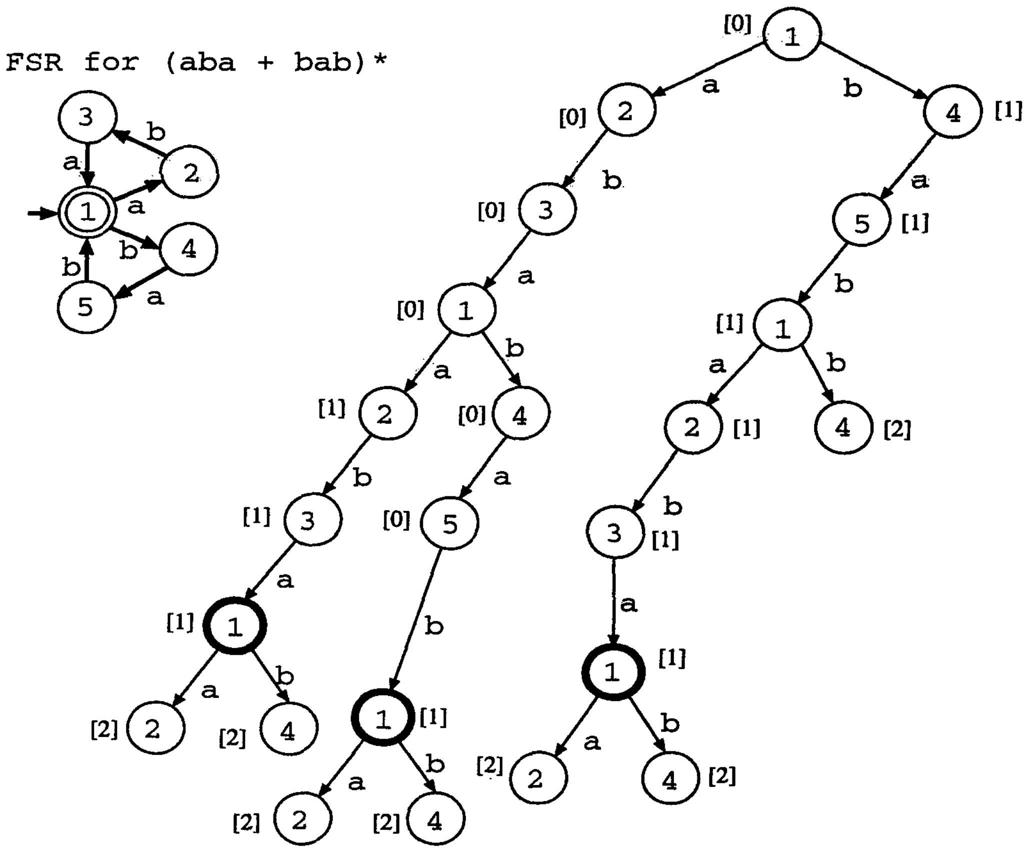
Figure 4
Computation of the elements of the H matrix.

length n. During backtracking, the entries for the last column are discarded, but the entries in prior columns are still valid. Thus, all entries required by $H(i+1,j+1)$, except $H(i,j+1)$, are already available in the matrix in columns $i-1$ and i. The computation of $cuted(X[m],Y[n])$ involves a loop in which the minimum is computed. This loop (indexing along column $j+1$) computes $H(i,j+1)$ before it is needed for the computation of $H(i+1,j+1)$.

We present in Figure 5 an example of this search algorithm for a simple finite-state recognizer for the regular expression $(aba+bab)^*$, and the search graph for the input string *ababa*. The thick circles from left to right indicate the nodes at which we have the matching strings *abaaba*, *ababab*, and *bababa*, respectively. Prior visits to the final state 1 violate the final edit distance constraint. (Note that the visit order of siblings depends on the order of the outgoing arcs from a state.)

3. Application to Error-tolerant Morphological Analysis

Error-tolerant finite-state recognition can be applied to morphological analysis. Instead of rejecting a given misspelled form, the analyzer attempts to apply the morphological analysis to forms that are within a certain (configurable) edit distance of the incorrect form. Two-level transducers (Karttunen and Beesley 1992; Karttunen, Kaplan, and Zaenen 1992) provide a suitable model for the application of error-tolerant recognition. Such transducers capture all morphotactic and morphographemic phenomena, as well as alternations in the language, in a uniform manner. They can be abstracted as finite-state transducers over an alphabet of lexical and surface symbol pairs l:s, where either



Search graph for matching ababa with threshold 1

Figure 5
Recognizer for $(aba + bab)^*$ and search graph for *ababa*.

l or s (but not both) may be the null symbol 0. It is possible to apply error-tolerant recognition to languages whose word formations employ productive compounding, or agglutination, or both. In fact, error-tolerant recognition can be applied to any language whose morphology has been described completely as one (very large) finite-state transducer. Full-scale descriptions using this approach already exist for a number of languages such as English, French, German, Turkish, and Korean (Karttunen 1994).

Application of error-tolerant recognition to morphological analysis proceeds as described earlier. After a successful match with a surface symbol, the corresponding lexical symbol is appended to the output gloss string. During backtracking the candidate surface string and the gloss string are again shortened in tandem. The basic algorithm for this case is given in Figure 6.[3] The actual algorithm is a slightly optimized version of this, in which transitions with null surface symbols are treated as special during forward and backtracking traversals to avoid unnecessary computations of the cut-off edit distance.

3 Note that transitions are now labeled with $l : s$ pairs.

```
/*push empty candidate string, and start node
to start search on to the stack */
push((ε, ε, q_0))
while stack not empty
    begin
      pop((surface', lexical', q_i)) /* pop partial strings
            and the node from the stack */
      for all q_j and l : s such that δ(q_i, l : s) = q_j
         begin /* extend the candidate string */
            surface = concat(surface', s)
            if cuted(X[m], surface[n]) ≤ t then
               begin
                   lexical = concat(lexical', l)
                   push((surface, lexical, q_j))
                   if ed(X[m], surface[n]) ≤ t and q_j ∈ F then
                     output lexical
               end
         end
    end
```

Figure 6
Algorithm for error-tolerant morphological analysis.

We can demonstrate error-tolerant morphological analysis with a two-level transducer for the analysis of Turkish morphology. Agglutinative languages, such as Turkish, Hungarian or Finnish, differ from languages like English in the way lexical forms are generated. Words are formed by productive affixations of derivational and inflectional affixes to roots or stems, like beads on a string (Sproat 1992). Furthermore, roots and affixes may undergo changes due to various phonetic interactions. A typical nominal or verbal root gives rise to thousands of valid forms that never appear in the dictionary. For instance, we can give the following (rather exaggerated) adverb example from Turkish:

uygarlaştıramayabileceklerimizdenmişsinizcesine

whose root is the adjective *uygar* 'civilized'.[4] The morpheme breakdown (with morphological glosses underneath) is:[5]

uygar	*+laş*	*+tır*	*+ama*	*+yabil*	*+ecek*
civilized	+AtoV	+CAUS	+NEG	+POT	+VtoA(AtoN)
+ler	*+imiz*	*+den*	*+miş*	*+siniz*	*+cesine*
+3PL	+POSS-1PL	+ABL(+NtoV)	+PAST	+2PL	+VtoAdv

The portion of the word following the root consists of 11 morphemes, each of which either adds further syntactic or semantic information to, or changes the part-of-speech of, the part preceding it. Although most words used in Turkish are considerably shorter than this, this example serves to point out that the nature of word structure in Turkish and other agglutinative languages is fundamentally different from word structure in languages like English.

Our morphological analyzer for Turkish is based on a lexicon of about 28,000 root

4 This is a manner adverb meaning roughly '(behaving) as if you were one of those whom we might not be able to civilize.'

5 Glosses in parentheses indicate derivations not explicitly indicated by a morpheme.

words and is a re-implementation, using Xerox two-level transducer technology (Karttunen and Beesley 1992), of an earlier version of the same description by the author (Oflazer 1993) (using the PC-KIMMO environment [Antworth 1990]). This description of Turkish morphology has 31 two-level rules that implement the morphographemic phenomena, such as vowel harmony and consonant changes across morpheme boundaries, and about 150 additional rules, again based on the two-level formalism, that fine-tune the morphotactics by enforcing long-distance feature sequencing and co-occurrence constraints. They also enforce constraints imposed by standard alternation linkage among various lexicons to implement the paradigms. Turkish morphotactics is circular, due to the presence of a relativization suffix in the nominal paradigm and multiple causative suffixes in the verb paradigm. There is also considerable linkage between nominal and verbal morphotactics, because derivational suffixation is productive. The minimized finite-state transducer constructed by composing the transducers for root lexicons, morphographemic rules, and morphotactic constraints, has 32,897 states and 106,047 transitions, with an average fan-out of about 3.22 transitions per state (including transitions with null surface symbols). It analyzes a given Turkish lexical form into a sequence of **feature-value tuples** (instead of the more conventional sequence of morpheme glosses) that are used in a number of natural language applications. The Xerox software allows the resulting finite-state transducer to be exported in a tabular form, which can be imported to other applications.

This transducer has been used as input to an analyzer implementing the error-tolerant recognition algorithm in Figure 6. The analyzer first attempts to parse the input with $t = 0$, and if it fails, relaxes t up to 2 if it cannot find any parse with a smaller t. It can process about 150 (correct) forms a second on a SPARCstation 10/41.[6] Below, we provide a transcript of a run:[7]

```
ENTER WORD > eva
Threshold 0 ... 1 ...


ela     =>  ((CAT ADJ)(ROOT ela))
evla    =>  ((CAT ADJ)(ROOT evla))
ava     =>  ((CAT NOUN)(ROOT av)(AGR 3SG)(POSS NONE)(CASE DAT))
deva    =>  ((CAT NOUN)(ROOT deva)(AGR 3SG)(POSS NONE)(CASE NOM))
eda     =>  ((CAT NOUN)(ROOT eda)(AGR 3SG)(POSS NONE)(CASE NOM))
ela     =>  ((CAT NOUN)(ROOT ela)(AGR 3SG)(POSS NONE)(CASE NOM))
enva    =>  ((CAT NOUN)(ROOT enva)(AGR 3SG)(POSS NONE)(CASE NOM))
reva    =>  ((CAT NOUN)(ROOT reva)(AGR 3SG)(POSS NONE)(CASE NOM))
evi     =>  ((CAT NOUN)(ROOT ev)(AGR 3SG)(POSS NONE)(CASE ACC))
eve     =>  ((CAT NOUN)(ROOT ev)(AGR 3SG)(POSS NONE)(CASE DAT))
ev      =>  ((CAT NOUN)(ROOT ev)(AGR 3SG)(POSS NONE)(CASE NOM))
evi     =>  ((CAT NOUN)(ROOT ev)(AGR 3SG)(POSS 3SG)(CASE NOM))
eza     =>  ((CAT NOUN)(ROOT eza)(AGR 3SG)(POSS NONE)(CASE NOM))
leva    =>  ((CAT NOUN)(ROOT leva)(AGR 3SG)(POSS NONE)(CASE NOM))
neva    =>  ((CAT NOUN)(ROOT neva)(AGR 3SG)(POSS NONE)(CASE NOM))
ova     =>  ((CAT NOUN)(ROOT ova)(AGR 3SG)(POSS NONE)(CASE NOM))
ova     =>  ((CAT VERB)(ROOT ov)(SENSE POS)(MOOD OPT)(AGR 3SG))

ENTER WORD > akıllınnikiler
```

6 No attempt was made to compress the finite-state recognizer. The Xerox *infl* program working on the proprietary compressed representation of the same transducer can process about 1,000 forms/sec on the same platform.

7 The outputs have been slightly edited for formatting. The feature names denote the usual morphosyntactic features. CONV denotes derivations to the category indicated by the second token with a suffix or derivation type denoted by the third token, if any.

```
Threshold 0 ... 1 ... 2 ...



akıllınınkiler =>
            ((CAT NOUN)(ROOT akıl)(CONV ADJ LI)
                  (CONV NOUN)(AGR 3SG) (POSS NONE)(CASE GEN)
                  (CONV PRONOUN REL)(AGR 3PL)(POSS NONE)(CASE NOM))
akıllınınkiler =>
            ((CAT NOUN)(ROOT akıl)(CONV ADJ LI)
                  (CONV NOUN)(AGR 3SG)(POSS 2SG)(CASE GEN)
                  (CONV PRONOUN REL)(AGR 3PL)(POSS NONE)(CASE NOM))
akıllındakiler =>
            ((CAT NOUN)(ROOT akıl)(CONV ADJ LI)
                  (CONV NOUN)(AGR 3SG)(POSS 2SG)(CASE LOC)
                  (CONV ADJ REL)
                  (CONV NOUN)(AGR 3PL)(POSS NONE)(CASE NOM))


ENTER WORD > eviminkinn
Threshold 0 ... 1 ...



eviminkini =>
            ((CAT NOUN)(ROOT ev)(AGR 3SG)(POSS 1SG)(CASE GEN)
                  (CONV PRONOUN REL)(AGR 3SG)(POSS NONE)(CASE ACC))
eviminkine =>
            ((CAT NOUN)(ROOT ev)(AGR 3SG)(POSS 1SG)(CASE GEN)
                  (CONV PRONOUN REL)(AGR 3SG)(POSS NONE)(CASE DAT))
eviminkinin =>
            ((CAT NOUN)(ROOT ev)(AGR 3SG)(POSS 1SG)(CASE GEN)
                  (CONV PRONOUN REL)(AGR 3SG)(POSS NONE)(CASE GEN))

ENTER WORD > teeplerdeki
Threshold 0 ... 1 ...



tepelerdeki =>
            ((CAT NOUN)(ROOT tepe)(AGR 3PL)(POSS NONE)(CASE LOC)
                  (CONV ADJ REL))
teyplerdeki =>
            ((CAT NOUN)(ROOT teyb)(AGR 3PL)(POSS NONE)(CASE LOC)
                  (CONV ADJ REL))


ENTER WORD > uygarlaştıramadıklarmıızdanmışsınızcasına
Threshold 0 ... 1 ...



uygarlaştıramadıklarımızdanmışsınızcasına =>
            ((CAT ADJ)(ROOT uygar)(CONV VERB LAS)(VOICE CAUS)(SENSE NEG)
                  (CONV ADJ DIK)(AGR 3PL)(POSS 1PL)(CASE ABL)
                  (CONV VERB)(TENSE NARR-PAST)(AGR 2PL)
                  (CONV ADVERB CASINA)(TYPE MANNER))


ENTER WORD > okatulna
Threshold 0 ... 1 ... 2 ...
```

```
okutulma =>
            ((CAT VERB)(ROOT oku)(VOICE CAUS)(VOICE PASS)(SENSE NEG)
                  (MOOD IMP)(AGR=2SG))
okutulma =>
            ((CAT VERB)(ROOT oku)(VOICE CAUS)(VOICE PASS)(SENSE POS)
                  (CONV NOUN MA)(TYPE INFINITIVE)
                  (AGR 3SG)(POSS NONE)(CASE NOM))
okutulan =>
            ((CAT VERB)(ROOT oku)(VOICE CAUS)(VOICE PASS)(SENSE POS)
                  (CONV ADJ YAN))
okutulana =>
            ((CAT VERB)(ROOT oku)(VOICE CAUS)(VOICE PASS)(SENSE POS)
                  (CONV ADJ YAN)(CONV NOUN)(AGR 3SG)(POSS NONE)(CASE DAT))
okutulsa => ((CAT VERB)(ROOT oku)(VOICE CAUS)(VOICE PASS)(SENSE POS)
                  (MOOD COND)(AGR 3SG))
okutula =>
            (CAT VERB)(ROOT oku)(VOICE CAUS)(VOICE PASS)(SENSE POS)
                  (MOOD OPT)(AGR 3SG))
```

In an application context, the candidates that are generated by such a morphological analyzer can be disambiguated or filtered to a certain extent by constraint-based tagging techniques (see Oflazer and Kuruöz 1994; Voutilainen and Tapanainen 1993) that take into account syntactic context for morphological disambiguation.

4. Applications to Spelling Correction

Spelling correction is an important application for error-tolerant recognition. There has been substantial work on spelling correction (see the excellent review by Kukich [1992]). All methods essentially enumerate plausible candidates that resemble the incorrect word, and use additional heuristics to rank the results.[8] Most techniques assume a word list of all words in the language. These approaches are suitable for languages like English, for which it is possible to enumerate such a list. They are not directly suitable or applicable to languages like German, which have very productive compounding, or agglutinative languages like Finnish, Hungarian, or Turkish, in which the concept of a word is much larger than what is normally found in a word list. For example, Finnish nouns have about 2,000 distinct forms, while Finnish verbs have about 12,000 forms (Gazdar and Mellish 1989, 59–60). Turkish is similar: nouns, for instance, may have about 170 different forms, not counting the forms for adverbs, verbs, adjectives, or other nominal forms, generated (sometimes circularly) by derivational suffixes. Hankamer (1989) gives much higher figures (in the millions) for Turkish; presumably he took derivations into account in his calculations.

Some recent approaches to spelling correction have used morphological analysis techniques. Veronis (1988) presents a method for handling quite complex combinations of typographical and phonographic errors (phonographic errors are the kind usually made by language learners using computer-aided instruction). This method takes into account phonetic similarity, in addition to standard errors. Aduriz et al. (1993) present a two-level morphology approach to spelling correction in Basque. They use two-level rules to describe common insertion and deletion errors, in addition to the two-level rules for the morphographemic component. Oflazer and Güzey (1994) present a two-level morphology approach to spelling correction in agglutinative languages using a coarser morpheme-based morphotactic description rather than the finer lexi-

8 Ranking is dependent on the language, the application, and the error model. It is an important component of the spelling correction problem, but is not addressed in this paper.

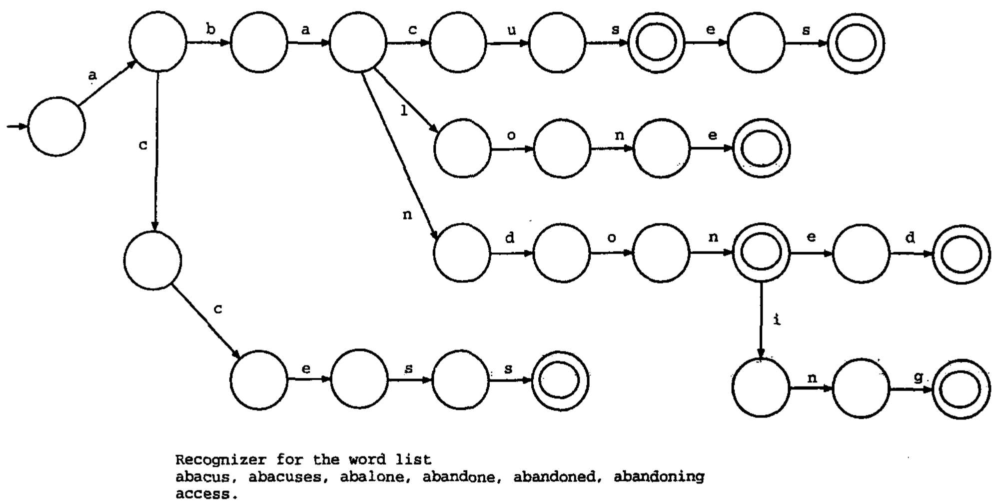


Figure 7
A finite-state recognizer for the word list: *abacus, abacuses, abalone, abandone, abandoned, abandoning, access.*

cal/surface symbol approach presented here. The approach presented in Oflazer and Güzey 1994 generates a valid sequence of the lexical forms of root and suffixes and uses a separate morphographemic component that implements the two-level rules to derive surface forms. However, that approach is very slow, mainly because of the underlying PC-KIMMO morphological analysis and generation system, and cannot deal with compounding because of its approach to root selection. More recently, Bowden and Kiraz (1995) have used a multitape morphological analysis technique for spelling correction in Semitic languages which, in addition to insertion, deletion, substitution, and transposition errors, allows for various language-specific errors.

For languages like English, all inflected forms can be included in a word list, which can be used to construct a finite-state recognizer structured as a standard letter-tree recognizer (with an acyclic graph) as shown in Figure 7. Error-tolerant recognition can be applied to this finite-state recognizer. Furthermore, transducers for morphological analysis can be used for spelling correction, so the same algorithm can be applied to any language whose morphology has been described using such transducers. We demonstrate the application of error-tolerant recognition to spelling correction by constructing finite-state recognizers in the form of letter trees from large word lists that contain root and inflected forms of words for 10 languages, obtained from a number of resources on the Internet (Table 1). The Dutch, French, German, English (two different lists), Italian, Norwegian, Swedish, Danish, and Spanish word lists contained some or all inflected forms in addition to the basic root forms. The Finnish word list contained unique word forms compiled from a corpus, although the language is agglutinative.

For edit distance thresholds 1, 2, and 3, we selected 1,000 words at random from each word list and perturbed them by random insertions, deletions, replacements, and transpositions, so that each misspelled word had the required edit distance from the correct form. Kukich (1992), citing a number of studies, reports that typically 80% of misspelled words contain a single error of one of the unit operations, although

Table 1
Statistics about the word lists used.

Language	Words	Arcs	Average Word Length	Maximum Word Length	Average Fan-out
Finnish	276,448	968,171	12.01	49	1.31
English-1	213,557	741,835	10.93	25	1.33
Dutch	189,249	501,822	11.29	33	1.27
German	174,573	561,533	12.95	36	1.27
French	138,257	286,583	9.52	26	1.50
English-2	104,216	265,194	10.13	29	1.40
Spanish	86,061	257,704	9.88	23	1.40
Norwegian	61,843	156,548	9.52	28	1.32
Italian	61,183	115,282	9.36	19	1.84
Danish	25,485	81,766	10.18	29	1.27
Swedish	23,688	67,619	8.48	29	1.36

Table 2
Correction Statistics for Threshold 1.

Language	Average Misspelled Word Length	Average Correction Time (msec)	Average Time to First Solution (msec)	Average Number of Solutions Found	Average % of Space Searched
Finnish	11.08	45.45	25.02	1.72	0.21
English-1	9.98	26.59	12.49	1.48	0.19
Dutch	10.23	20.65	9.54	1.65	0.20
German	11.95	27.09	14.71	1.48	0.20
French	10.04	15.16	6.09	1.70	0.28
English-2	9.26	17.13	7.51	1.77	0.35
Spanish	8.98	18.26	7.91	1.63	0.37
Norwegian	8.44	16.44	6.86	2.52	0.62
Italian	8.43	9.74	4.30	1.78	0.46
Danish	8.78	14.21	1.98	2.25	1.00
Swedish	7.57	16.78	8.87	2.83	1.57
Turkish (FSR)	8.63	17.90	7.41	4.92	1.23

in specific applications the percentage of such errors is lower. Our earlier study of an error model developed for spelling correction in Turkish indicated similar results (Oflazer and Güzey 1994).

Tables 2, 3, and 4 present the results from correcting these misspelled word lists for edit distance thresholds 1, 2, and 3, respectively. The runs were performed on a SPARCstation 10/41. The second column in these tables gives the average length of the misspelled string in the input list. The third column gives the time in milliseconds to generate *all* solutions, while the fourth column gives the time to find the first solution. The fifth column gives the average number of solutions generated from the given misspelled strings with the given edit distance. Finally, the last column gives the percentage of the search space (that is, the ratio of forward-traversed arcs to the total number of arcs) that is searched when generating all the solutions.

Table 3
Correction Statistics for Threshold 2.

Language	Average Misspelled Word Length	Average Correction Time (msec)	Average Time to First Solution (msec)	Average Number of Solutions Found	Average % of Space Searched
Finnish	11.05	312.26	162.49	13.54	1.30
English-1	9.79	232.56	108.69	7.90	1.51
Dutch	10.24	148.62	68.19	9.35	1.25
German	12.05	169.88	96.55	3.33	1.14
French	9.88	95.07	37.52	6.99	1.44
English-2	9.12	129.29	55.64	12.56	2.28
Spanish	8.78	125.35	48.80	10.24	2.49
Norwegian	8.36	112.06	42.13	27.27	3.47
Italian	8.41	57.87	25.09	8.09	2.36
Danish	9.15	82.39	34.80	13.25	4.23
Swedish	7.44	90.59	16.47	36.37	6.84
Turkish (FSR)	8.59	164.81	57.87	55.12	11.12

Table 4
Correction Statistics for Threshold 3.

Language	Average Misspelled Word Length	Average Correction Time (msec)	Average Time to First Solution (msec)	Average Number of Solutions Found	Average % of Space Searched
Finnish	11.08	1217.56	561.70	157.39	3.86
English-1	9.73	1001.43	413.60	87.09	5.30
Dutch	10.30	610.52	256.90	71.89	4.07
German	11.82	582.45	305.80	21.39	3.14
French	9.99	349.41	122.38	41.58	4.00
English-2	9.36	519.83	194.69	97.24	6.97
Spanish	8.90	507.46	176.77	88.31	7.79
Norwegian	8.47	400.57	125.52	199.72	8.98
Italian	8.34	198.79	66.80	55.47	6.41
Danish	9.25	228.55	47.9	97.85	8.69
Swedish	7.69	295.14	36.89	267.51	14.70
Turkish (FSR)	8.57	907.02	63.59	442.17	60.00

4.1 Spelling Correction for Agglutinative Word Forms

The transducer for Turkish developed for morphological analysis, using the Xerox software, was also used for spelling correction. However, the original transducer had to be simplified into a recognizer for two reasons. First, for morphological analysis, the concurrent generation of the lexical gloss string requires that occasional transitions with an empty surface symbol be taken to generate the gloss properly. Secondly, in morphological analysis, a given surface form may have many morphological interpretations. This diversity must be accounted for in morphological processing. In spelling correction, however, the presentation of only one surface form is sufficient. To remove all empty transitions and analyses with the same surface form from the Turkish transducer, a recognizer recognizing only the surface forms was extracted using the Xerox tool *ifsm*. The resulting recognizer had 28,825 states and 118,352 transitions labeled with just surface symbols. The average fan-out of the states in this recognizer was about 4. This transducer was then used to perform spelling correction experiments in Turkish.

In the first set of experiments, three word lists of 1,000 words each were generated from a Turkish corpus, and words were perturbed as described before, for error thresholds of 1, 2, and 3, respectively. The results for correcting these words are presented in the last rows (labeled Turkish [FSR]) of the tables above. It should be noted that the percentage of search space searched may not be very meaningful in this case since the same transitions may be taken in the forward direction more than once.

In a separate experiment that would simulate a real correction application, about 3,000 misspelled Turkish words (again compiled from a corpus) were processed by successively relaxing the error threshold starting with $t = 1$. Of this set of words, 79.6% had an edit distance of 1 from the intended correct form, while 15.0% had an edit distance of 2, and 5.4% had an edit distance of 3 or more. The average length of the incorrect strings was 9.63 characters. The average correction time was 77.43 milliseconds (with 24.75 milliseconds for the first solution). The average number of candidates offered per correction was 4.29, with an average of 3.62% of the search space being traversed, indicating that this is a very viable approach for real applications. For comparison, the same recognizer running as a spell checker ($t = 0$) can process correct forms at a rate of about 500 words/sec.

5. Conclusions

This paper has presented an algorithm for error-tolerant finite-state recognition that enables a finite-state recognizer to recognize strings that deviate mildly from some string in the underlying regular set. Results of its application to error-tolerant morphological analysis and candidate generation in spelling correction were also presented. The approach is very fast and applicable to any language with a list of root and inflected forms, or with a finite-state transducer recognizing or analyzing its word forms. It differs from previous error-tolerant finite-state recognition algorithms in that it uses a given finite-state machine, and is more suitable for applications where the number of patterns (or the finite-state machine) is large and the string to be matched is small.

In some cases, however, the proposed approach may not be efficient and may be augmented with language-specific heuristics: For instance, in spelling correction, users (at least in Turkey, as indicated by our error model [Oflazer and Güzey 1994]) usually replace non-ASCII characters with their nearest ASCII equivalents because of inconveniences such as nonstandard keyboards, or having to input the non-ASCII characters using a sequence of keystrokes. In the last spelling correction experiment for Turkish, almost all incorrect forms with an edit distance of 3 or more had three or more non-ASCII Turkish characters, all of which were rendered with the nearest ASCII version (e.g., *yaşgünümüzde* (on our birthday) was written as *yasgunumuzde*). These forms could surely be found with appropriate edit distance thresholds, but at the cost of generating many words containing more substantial errors. Under these circumstances, one may use language-specific heuristics first, before resorting to error-tolerant recognition, along the lines suggested by morphological-analysis-based approaches (Aduriz et al. 1993; Bowden and Kiraz 1995).

Although the method described here does not handle erroneous cases where omission of space characters causes joining of otherwise correct forms (such as *inspite of*), such cases may be handled by augmenting the final state(s) of the recognizers with a transition for space characters and ignoring all but one of such space characters in the edit distance computation.

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