Integration of an on-line handwriting recognition system in a smart phone device

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Abstract

This paper presents the evolving of our academic development to a technology driven application: the integration of an unconstraint cursive on-line handwritten character recognition system into a smart phone device. The ultimate goal of this work is to implement an accuracy handwriting recognizer into mobile devices with limited computing and memory resources. A hierarchical fuzzy modeling is used to obtain a compact and robust knowledge representation and the decision process is based on an adapted fuzzy inference system to reduce computing without decreasing the performances. We describe in this paper the basic architecture of the recognition system called "ResifCar", its practical adaptation to the mobile device constraints and the recognition rates both on cursive isolated letters (91.9%) and on isolated digits (92.3%) in a writer independent context based on 100 different writers.

1. Introduction

On-line systems for handwriting recognition take an important place in the newer technologies around hand-held computers. These new mobile devices are personal tools small enough to be carried everywhere. Most popular are personal digital assistants (PDAs) and soon the next generation of mobile phones, called "smart phone", which combine the functionality of a mobile phone with that of a PDA.

Several handwriting recognition systems have been yet integrated in mobile devices. They can be characterized by the constraint environment the handwriting recognition is processed, the character set that can be recognized, the writing styles they are able to deal with, the CPU and memory requirements, and the recognition rates they can achieved in a writer independent context.

It is still today a real research challenge to design a handwriting recognition system able to overcome all these interdependent problems [2][3]. In this way, we have collaborated during one year with an industrial partner (2) specialized in the development of mobile handsets. The aim of this collaboration is to optimize and integrate our handwritten character recognition system called "ResifCar" into a smart phone device.

"ResifCar" is a writer independent on-line handwriting recognition system able to deal with cursive handwritten characters. It is the result of our(1) last 10 years researches [1][6][7].

This paper describes the adaptation and the optimization of ResifCar for its integration into a smart phone device based on ARM 7 TDMI microprocessor. In the context of this practical implementation, the recognizer must compute into a device with limited resources : 13 Mhz CPU, RAM size of 50 Kbytes and ROM size (program and data) around 200 Kbytes available for this feature.

Moreover the input method which combines LCD display with a digitizer is based on a low tactile screen definition (0.20 mm pixel pitch) with a sampling frequency of 20 points per second.

In Parallel with these practical constraints, the key goals for the on-line recognizer are:

· unconstrained handwriting recognition: be able to deal with the shape variations of a single character coming from the different writing styles (allographs, see Table 1);
· reliable recognition of cursive isolated handwritten characters: Latin alphabet, digits and other special symbols;

· writer independent recognition: no need to have user training before the recognition can start;
· multi-strokes character recognition;
· easy extension of the recognizer with new character models.

The following section presents the principles of the recognition system ResifCar. Then, section 3 describes the adaptation and optimization of the recognizer for its integration into the mobile device with limited resources. Section 4 presents results both on the recognition rates and on the practical integration aspects such as computation time and memory size.

2. Recognition system: ResifCar

ResifCar is based on a hierarchical fuzzy modeling of each character class [6]. This intrinsic modeling provides a robust description of the most pertinent primitive shapes that define a character class. The shape primitives are automatically extracted from a character drawing both from perceptually important points called singularities or perceptually anchorage points and from dynamic information such as ductus [2][7].

The hierarchical architecture (cf. Figure 1) of each model is represented by three general levels *(L1, L2, L3)* structured according to their robustness and pertinence [2][6]. The first level models the most pertinent downstrokes primitives which are known to be one of the most invariant and robust part of the handwriting drawing. The second level refines the description of downstrokes by modeling their morphological context. And finally, the last level represents beginnings and ends of the character shape often called ligatures. The interdependence of the knowledge represented in the three levels is formalized by a fuzzy prototype tree.

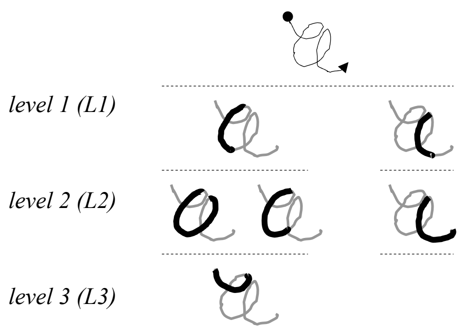


Figure 1. Partial example of 3 hierarchical representation levels illustrated for a letter "a".

The learning process is operated for each character class using a training data base. This automatic process generates successively the three representation levels. The key paradigm of the learning process is to extract and model automatically the most pertinent shape primitives by using possibilistic clustering [4][5] in a feature space according to each of the three representation levels. Possibilistic clustering generates fuzzy ellipsoidal prototypes that model the typicality of the most pertinent primitives sets.

After the learning phase, the automatic fuzzy modeling process [6] formalizes the knowledge by explicit fuzzy rules as follows:

$$
\begin{aligned}
\mathbf{r}^k: \textbf{ if } (\ &((x^{L1}_{1} \text{ is } m^{k,L1}_{11} \textbf{ and...and } x^{L1}_{r} \text{ is } m^{k,L1}_{1r})\\
&\quad \textbf{and/or } (x^{L1}_{1} \text{ is } m^{k,L1}_{21} \textbf{ and...and } x^{L1}_{r} \text{ is } m^{k,L1}_{2r}) \textbf{ and/or...})\\
&\textbf{and}((x^{L2}_{1} \text{ is } m^{k,L2}_{11} \textbf{ and...and } x^{L2}_{s} \text{ is } m^{k,L2}_{1s})\\
&\quad \textbf{and/or } (x^{L2}_{1} \text{ is } m^{k,L2}_{21} \textbf{ and...and } x^{L2}_{s} \text{ is } m^{k,L2}_{2s}) \textbf{ and/or...})\\
&\textbf{and}((x^{L3}_{1} \text{ is } m^{k,L3}_{11} \textbf{ and...and } x^{L3}_{t} \text{ is } m^{k,L3}_{1t})\\
&\quad \textbf{and/or } (x^{L3}_{1} \text{ is } m^{k,L3}_{21} \textbf{ and...and } x^{L3}_{t} \text{ is } m^{k,L3}_{2t}) \textbf{ and/or...})\\
&)\\
&\textbf{then } \textit{the unknown pattern} \text{ belongs}\\
&\quad \text{to class } c^k \textbf{ and not } \textit{to the others,}
\end{aligned}
$$

where $\mathbf{r}^k$ is the rule which characterizes the class c^k, $(x^{Lj}_{1}, ..., x^{Lj}_{r})$ is the input vector of feature space of level *Lj*, $(m^{kLj}_{\alpha 1}, ..., m^{kLj}_{\alpha r})$ are the corresponding fuzzy membership functions relative to each feature, where $m^{k\,Lj}_{\alpha\beta}$ is defined by a bell-shaped function which models the prototype P^{kLj}_{α} according to the feature x^{Lj}_{β}.

The number of prototype $P^{k\,Lj}_{\alpha}$ extracted for each level *Lj* is automatically estimated by the possibilistic clustering. That means several robust types of primitive shapes can be modeled for each representation level to cope with different drawings of a same character (often called allographs) according to different handwriting styles (see Table 1).

It is important to notice the interdependence of each three parts of the premises according to the level description *(L1, L2, L3)*. In fact, each rule premise is dynamically builds from level one to level three according to the adequacy between the unknown character shape and the hierarchical fuzzy prototype tree.

All the n fuzzy rules $\mathbf{r}^k$ generated for each class c^k are aggregated in a fuzzy inference system to compose the decision process. The fuzzy inference process is computed with the sum-product inference method defined by:

$$y'_k = \frac{\sum_{i=1}^{n} \rho_i \times \delta_{ik}}{\sum_{i=1}^{n} \rho_i} \quad \text{with} \quad \rho_k = \prod_{Lj,\alpha,\beta} m^{k,Lj}_{\alpha\beta}(x'^{Lj}_{\beta}),$$

where y'_k is the adequacy measure of model k with the unknown character, δ_{ik} the kronecker symbol that defines output i of the fuzzy rule $\mathbf{r}^k$, and ρ^k the activation value of the rule $\mathbf{r}^k$. ρ^k is calculated by the product conjunction of all membership degree of input feature x'^{Lj}_{β} to the corresponding fuzzy membership function $m^{k\,Lj}_{\alpha\beta}$. In case of disjunction in the premise part *max* operator is used.

This intrinsic modeling process allows to add new character classes without rebuilding all existing models. Moreover, the fuzzy modeling is very robust with respect to intra class variability. Then, the recognizer is able to deal with allographic variation as illustrated in Section 4.

3. Adaptation and optimization

To integrate ResifCar into the mobile device we need to overcome the limitation of computing and memory resources without imposing new handwriting constraints and without decreasing recognition rates. The recognition time depends on the size of the model set. Therefore, to speed up the recognition, a pre-selection is performed thanks to the transparent (explicit) design of the hierarchical fuzzy modeling. The decision process is optimized by a pre-selection of models according to the first representation level which is based on the most stable shape primitives. The selection of the best-N models is operated as follows:

$$\text{model } i \quad \text{is selected} \quad \text{if} \quad \rho_{L1,i} \geq \frac{\max\limits_{k=1,n}(\rho_{L1,k})}{S_{L1}},$$

where $\rho^{L1,k}$ is the level *one* ($L1$) activation value of the rule $\mathbf{r}^k$ (model k) and S_{L1} the threshold of selection. This pre-selection is very reliable and experimentally around 70% of models are pruned in average by the pre-selection process. Then, the continuation of the decision process is operated on a reduced number of models both for second and third level representations.

Other practical adaptations have been done to limit computing and memory size. For instance fuzzy inference process is traduced in *logarithms* to avoid multiplication operations which are very computing expensive. Moreover fuzzy membership functions have been tabulated in their logarithmic form and all numerical features were coded by integer numbers. Simplified fuzzy inference is now computed as follows:

$$\dot{y}_k = \dot{\rho}_k \quad \text{with} \quad \dot{\rho}_k = \sum_{Lj,\alpha,\beta} \dot{m}^{k,Lj}_{\alpha\beta}(\dot{x}^{Lj}_{\beta}),$$

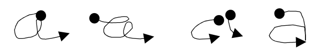
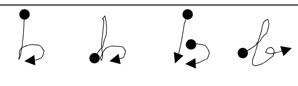
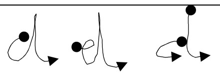
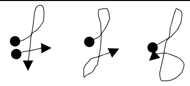
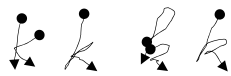
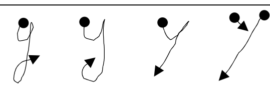
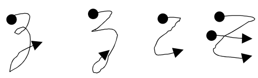
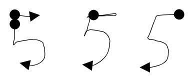
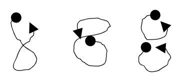
where $\dot{y}_k$ is the new adequacy measure of model k with the unknown character, and $\dot{\rho}_k$ the new activation value of the rule $\mathbf{r}^k$ calculated by the summation of all logarithmic membership degree of the input feature $\dot{x}$ using the corresponding tabulated fuzzy logarithmic membership function $\dot{m}$.

This new adequacy measure $\dot{y}_k$ is no more normalized and directly used by the decision process to classify the N-best models.

4. Experiments and results

The experiments have been conducted on the optimized ResifCar recognizer which has been implemented into the Arm7 TDMI microprocessor of the smart phone device. Two experimental results are reported: one on isolated cursive lower-case letters with special symbols and the other on isolated cursive digits. The leaning process was conducted on 63 different classes for the 26 letters and special symbols: @, &, €, $, ¥, £. For the 10 digits, 26 models have been generated. The aim is to offer the most unconstrained handwriting recognition able to cope with a great set of writing styles. Table 1 illustrates the capability of the recognizer to identify different allographic shapes.

Table 1. Examples of different allographic shapes recognized by ResifCar.

classes	allograph examples → stroke beginning •— stroke end
a	 …
b	 …
d	 …
f	 …
k	 …
y	 …
z	 …
5	 …
8	 …

The experiments were carried out on a data base composed of 15000 isolated characters written down by around 300 different writers. The models were automatically learned from samples coming from 200 different writers, and the samples from the 100 others writers were used for test experiments. Our experimental recognition results are summarized in Table 2.

Table 2. Writer independent recognition rates on isolated handwritten characters

	Top one hypotheses	Top two hypotheses	Top three hypotheses
letters and special symbols	91.9%	96.4%	97.5%
digits	92.3%	94.8%	96.3%

It is interesting to notice that the modeling process initially developed for handwritten letters recognition was then directly applied to handwritten digits recognition. This shows the good genericity and adaptation capability of the proposed modeling process for the recognition of different kinds of handwritten shapes.

The performance of the recognition system concerning computing and memory resources are reported in Table 3 and Table 4. These figures can appear very high for a single feature in such a device but the algorithm performances are quite good compared to the same feature performances in other products. What it is important to say, it is that the algorithm permits to recognized multi-strokes characters.

Table 3. Memory resources sizes

	memory size (Rom)	memory size (Ram)
Recognition system	48 KB	31.6 KB
the 63+26 character models	60.9 KB	

Table 4. Computing performance

	real time computing without optimizations	real time computing with optimizations
a letter “t”	9 s	0.62 s
a letter “a”	11 s	0.49 s
in average considering all the models	11 s	0.5 s

Recognition rates on isolated characters are significant due to the facts that the recognition is done without any context (many letters and digits can be confused: *h, k* and *e, l* and *r, v* and *1, 7* etc.) and that the computing and memory resources of the device are very limited. Moreover, they are already sufficient for using the recognition system as a friendly and practical handwriting input device.

5. Conclusions and future work

This paper has presented a real integration into a mobile phone of an unconstrained handwritten cursive character recognizer called ResifCar. Experiments showed the robustness and the compactness of the intrinsic hierarchical fuzzy modeling. Furthermore the decision process has been optimized to achieve reliable recognition both on isolated cursive characters and on digits with limited computing and memory resources.

Work is in progress to extend the capability of the recognition system to unconstrained cursive handwritten words. In fact, this system is almost operational [7] but needs to be adapted and optimized in the same way as shown in this paper to overcome the computing and memory limitations of hand-held devices.

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