A Neural Network Approach to Handwritten Curve Partitioning

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Abstract

Handwritten curve partitioning is a key problem in character recognition and signature verification. Methods have already been proposed to localize segmentation points on a continuous planar curve. This paper suggests a neural network approach for the parallel processing of all the points of the curve to be partitioned. Each output node of the network corresponds to a point of the curve and produces a value that reflects the perceptual importance of that point in relation to its neighbors. The neighborhood of a point is dynamically defined according to local geometric criteria. The segmentation points are those that are associated with the output neurons having the locally highest value. The approach is explained and examples are given.

1. Introduction

The research being carried out in handwritten curve analysis is relating to the perfecting of a number of types of application in the field of man-machine communications: character recognition systems [Berthod82, Tappert88], signature verification [Plamondon89], electronic publishing [Brocklehurst91], etc. The majority of methods used in the curve analysis require the prior partitioning of the curves to be processed in order to ensure the adequate execution of the characterization and shape comparison procedure: for example, the recognition of a word requires the recognition of its constituent letters, each letter being composed of a set of characteristic attributes, etc.

This is also true in the case of some signature verification methods: preprocessing (partitioning) must be carried out in order to isolate the segments of which a signature is composed and to compare their space-time characteristics to those of the segments that make up the reference signature.

The aim of the partitioning operation described here is to find a minimum number of points that would, for example, enable an imitator to reproduce the signature [Brault93]. Several methods have been proposed for partitioning continuous planar curves. It is possible, for example, to approximate the curve, in several successive steps, with a minimum number of straight-line segments (the "split & merge" method [Pavlidis74]). Another method is to calculate the local correlation between the curve to be partitioned and a mathematical model of a peak (or corner) that includes a given (and predefined) number of points (the "corner model" of [Kruse & Rao78]). It is also possible to measure the importance of each point relative to a given (and predefined) number of its neighbors [Freeman & Davis77]. This importance measure is obtained by calculating the curvature at the point of interest and the number of neighbors adjacent to it having a curvature less than a predetermined threshold.

[Brault93] has proposed a method, based on the Freeman and Davis method, for calculating the perceptual importance of the points of a curve in the signature verification domain. The approach is novel in its use of a variable window to study the importance of each point. Indeed, there can be problems with a fixed-dimension window, such as the possibility of including more than one potentially important point in the window (Figure 1a) or an incomplete importance calculation if the environment taken into account by the window is too restricted or to large (Figure 1b). Since the importance of a point depends on its entire environment, a variable-dimension window makes it possible to consider the pertinent environmental factors in calculating the importance of the point.

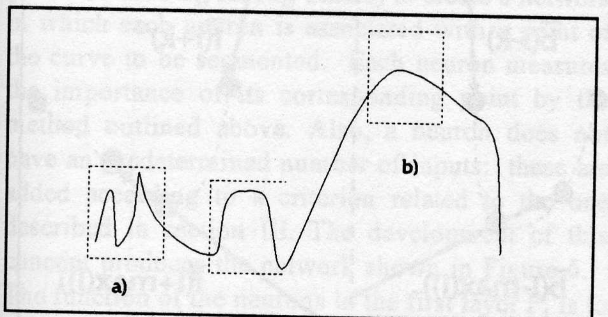

Figure 1: problems with fixed-size window

The parallel processing of the Brault algorithm may be achieved by means of a neural network by associating a neuron with each point of the curve, the output of which is the measure of the perceptual importance of the point according to its neighborhood. Well known architectures, such as the multi-layer network that is characteristic of back propagation, for example, are inadequate since their number of inputs is fixed and their use involves the implementation of a fixed-dimension analysis window. An alternative is proposed in this article, which is an architecture with a variable number of inputs, as illustrated in Figure 2.

In section II, the nature of the data is described, and some useful definitions connected with the data are presented; in section III, the importance measure of a point is introduced; in section IV, the proposed network and its characteristics are described; section V presents our results, and includes some observations on the performance of the network.

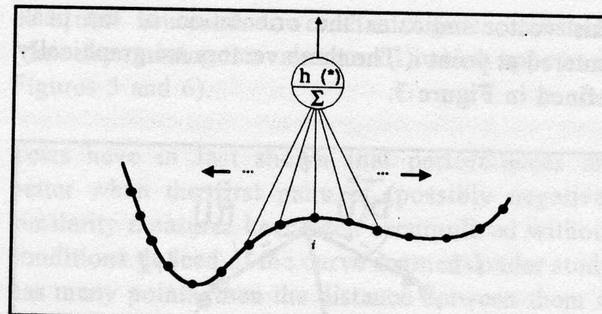

Figure 2 Importance measure of point i by a neuron

II. Nature of the data and definitions

The curves to be analyzed are made up of X-Y coordinates received from a digitizing tablet during the acquisition of handwritten signature. These data are filtered using a Gaussian low-pass filter [Wells86] and are then resampled using a cubic spline technique (described in [Press88]) in such a way as to produce a new curve in which the points are equidistant in the space domain.

A curve may be considered as a series of displacements carried out from one point to another. We first characterize a handwritten curve by concatenating a displacement of the first point to the second (forward displacement described by $\vec{f}(1)$, followed by a displacement to the third (described by $\vec{f}(2)$), etc., and, finally, a displa-cement towards the last point N (described by $\vec{f}(N-1)$). A vector $\vec{b}(i)$ (backward) is also defined for each point i, such that:

$$\vec{b}(i) = -\vec{f}(i-1) \qquad 2 \le i \le N$$

Since the points of the curve are equidistant, we consider the vectors normalized:

$$\|\vec{b}(i)\| = \|\vec{f}(i)\| = 1$$

A vector $\vec{n}(i)$ is then defined, which we call "normal" to the curve at point i:

$$\vec{n}(i) = \frac{\vec{b}(i) + \vec{f}(i)}{\|\vec{b}(i) + \vec{f}(i)\|}$$

This vector indicates the orientation of the peak centered at point i. The three vectors are graphically defined in Figure 3.

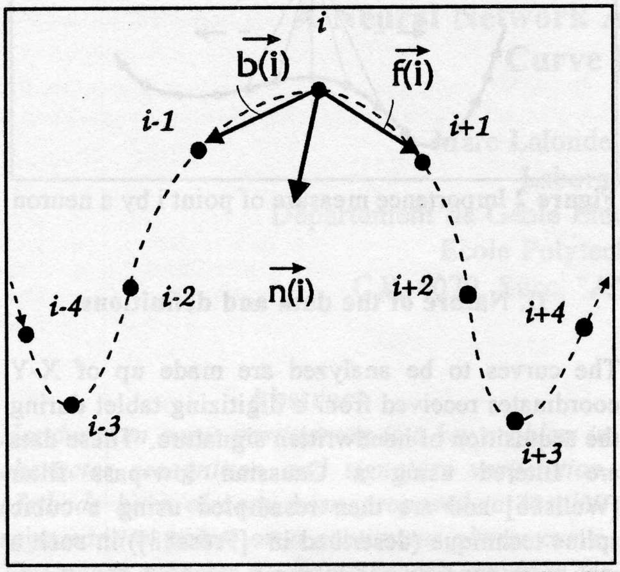

Figure 3 Definitions of the three vectors b(i), f(i) and n(i)

III. Measure of the importance of a point

The evaluation of the perceptual importance of a point i at the apex of a peak is based on the following two factors: the curvature at the apex of the peak and the length of its sides [Davis77], which means that the sharper the peak, the easier it is to locate the segmentation point.

Figure 4 shows that if a point i is at the apex of a sharp peak, then the orientation of the vectors $\vec{f}(i)$ and $\vec{b}(i)$ is very close to that of the normal $\vec{n}(i)$. This similarity is measured by the scalar product between each vector and the normal.

The importance of a point located at the apex of a peak is also a function of the length of the sides of the peak: the higher or the more stretched the peak, the more its apex becomes a singular point that must be retained. The natural tendency is to include in the importance calculation the contribution of the set of points that comprises the peak, that is, to evaluate the similarity between the vectors $\vec{b}(i-k)$ and $\vec{f}(i+k)$ and the normal $\vec{n}(i)$, where parameter "k" is the distance relative to point i (Figure 4).

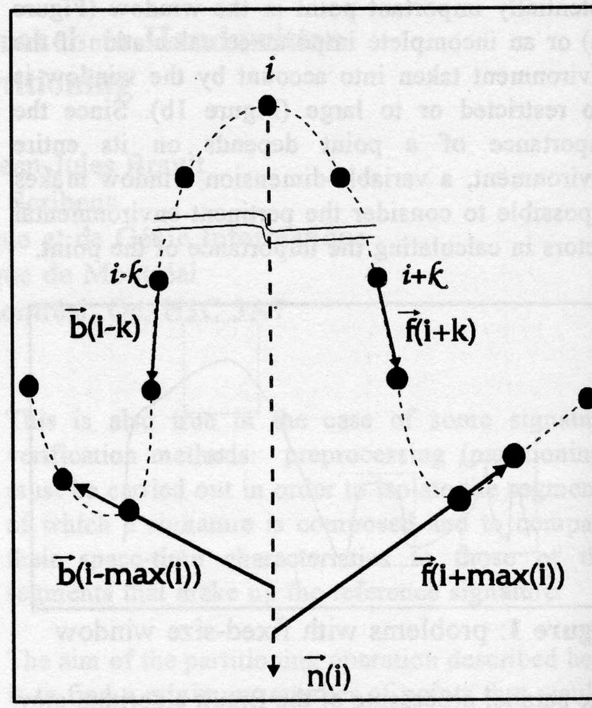

Figure 4 Accumulation limit

The measure of importance in i is then obtained through the accumulation of the similarity measures over a range where k varies from 0 to max(i), which depends on its neighborhood, is defined as follow. This accumulation process must be permitted as long as a particular criterion, which is related to the geometry of the curve, is respected. The base of the peak may be considered to have been reached when:

$$\vec{b}(i-k)\cdot\vec{n}(i) \leq \textit{positive threshold}$$

or

$$\vec{f}(i-k)\cdot\vec{n}(i) \leq \textit{positive threshold}$$

IV. Model of the network

It should be noted that the calculations for two neighboring points are completely independent (i.e. the importance of a point i has no influence on the measurement of the importance of point i+1) and that these calculations, which are described in the preceding section, are simple enough to be performed by a neural network (e.g. scalar products, summations and threshold operations). However, parallel processing can only be achieved by a network with a variable number of inputs (the purpose of the input variability condition is to give the window elasticity).

Since variable-input networks are extremely rare (or nonexistent), we have turned our interest toward dynamically constructed or adapted networks (e.g. the self-development neural network of [Lee & Peterson 90], Fahlman's cascade correlation [NeuralWare 91], among others) to create a network in which each neuron is associated with a point of the curve to be segmented. Each neuron measures the importance of its corresponding point by the method outlined above. Also, a neuron does not have an predetermined number of inputs: these are added according to a criterion related to the one described in section III. The development of this concept produces the network shown in Figure 5. The function of the neurons in the first layer F_1 is to produce a local measure of importance; neuron i of layer F_2 (associated with point i) calculates the sum of the contributions to produce a global measure of importance.

Inputs

The data sent from the digitizing tablet are converted into relative displacements (Δx, Δy). This conversion is shown schematically in Figure 5.

Layer F_1

The activation of neuron k is given by the scalar product between the input ($\Delta x_{i\pm k}$, $\Delta y_{i\pm k}$) and the weight vector ($n(i)_x$,$n(i)_y$), and represents a measure of the similarity of the orientation between the two vectors. This in turn makes it possible to evaluate the local contribution of the input vector to the measure of the importance of point i, according to the first criterion specified at the beginning of section III. Here we see the philosophy adopted by Kohonen for his Feature Maps model.

This layer has no predetermined dimension: neurons are added in pairs (Ub(k) and Uf(k)) as long as the cumulative-limit criterion has not been met. This criterion, reformulated for neural networks, may be expressed as follows: cumulative totalling is stopped at the moment when the output of a new neuron is lower than a given threshold (thus determining the value max(i) which appears in Figures 5 and 6).

Tests have in fact shown that performances are better when the first pairs of (possibly negative) similarity measures have been accumulated without conditions. Indeed, if the curve segment under study has many points, then the distance between them is small and they are nearly colinear, and the procedure stops right at the start because the condition for stopping it has already been met. This kind of ajustable hysteris allows the system to use the stop conditioonly when the distance from the central point i is such that the potential curvature of the curve begins to be felt.

The transfer function of the neuron, a sigmoid curve with a parameter θ (representing the minimal scalar product to obtain) to be adjusted, has been chosen in such a way as to enhance the strong similarity measures. This parameter has been adjusted empirically up to now, but a procedure for doing this will probably be developed eventually. However, its value could be taken from a wide range of values betwenn 0 and 1 (examples will be given at the presentation).

Layer F_2

This layer consists of linear transfer function neurons that are constructed in the same way as the sigma-pi units of [Rumelhart86] or the conjunctive units of [Feldman82]: their activation, which grows through the addition of neurons to layer F_1, is the sum of the outputs of the paired neurons (layer F_1) multiplied two by two:

$$Activation_i = \sum_{k=0}^{\max(i)} Out_{Ub(k)} Out_{Uf(k)}$$

Each point of the handwritten curve to be segmented is analyzed by a network of the type shown in Figure 6.

Determination of the segmentation points

All the points have a relative importance. The value of the associated neuron reflects this importance, and we find through simulation that the proposed structure ensures that these associated neurons (layer F_2) have fairly homogeneous variations (few local maxima), with higher values in regions of greater curvature and very small or null values on straight-line segments (depending on the value of θ). An easy way to determine the winners is to channel the outputs of layer F_2 into a procedural program that will detect the most active neurons in each grouping (see appendix for results).

Another way to identify them would be to think of the process as a competition that must take place among the neurons, and to consider the points associated with them as segmentation points. This would imply the addition of lateral (inhibiting) connections between the neurons of layer F_2 (those who are members of an active region).

The effects of these connections are not easy to control. Researchers, including [Grossberg76], [Amari82], [Grossberg80], [Kohonen89], [Feldman82], [Rumelhart85] and many others, have modeled them and incorporated them in their models. Our objective is to include all the neurons of a neighborhood in the competition, (a neighborhood being defined as a grouping of active units (with a positive output) surrounded by inactive units (with a null output), such that a single segmentation point emerges from each grouping). The ultimate challenge will be to remodel the nature of the neurons and the type of interconnections between them in order to avoid having to define neighborhoods.

V. Presentation of results

The figures in the appendix show the simulator interface used to set up the proposed network: window 1 (upper left) displays the curve to be segmented; window 2 (upper right) displays an enlargement of the curve at the point specified by the mouse; window 3 (lower left) displays the output of layer F_2 of the network (positioned in the same way as the original curve to facilitate viewing); and window 4 (lower right) displays the activation of the neuron of layer F_2 associated with specified point (this neuron will be referred to below as a PE(i)), and the activation of the neighboring neurons. As predicted, the colinear points induce weak activation in a PE(i), while at the apex of the sharp peaks, there is much stronger activation.

During a segmentation process, the location of an important point along a curve of small curvature is difficult to determine accurately. This is true of most of the segmentation algorithms, and the proposed neural network technique is no exception (examples will be shown at the presentation). Two effects influence the activation in a PE(i): the number of contributions permitted and the quality of each contribution (the importance of the numerical value of the quantity $b_k f_k$, in Figure 6). These effects depend on the neural transfer function of the F_1 layer, and thus the performances of the network are very closely connected with the quality of the design of this function and with the choice of θ. The next step in evaluating this approach is to find the best possible design and to compare its performance with that of the [Brault93] algorithm in terms of the number of proposed segmentation points and their position.

VI. Conclusion

This work represents the first step in the design of a signature verification system using neural networks, and its goal is to show that signature partitioning may be carried out by means of a connectionist tool that could eventually be implemented at the hardware level in the creation of a segmentation module for a handwritten curve (in a signature and eventually in cursive writing).

VII. References

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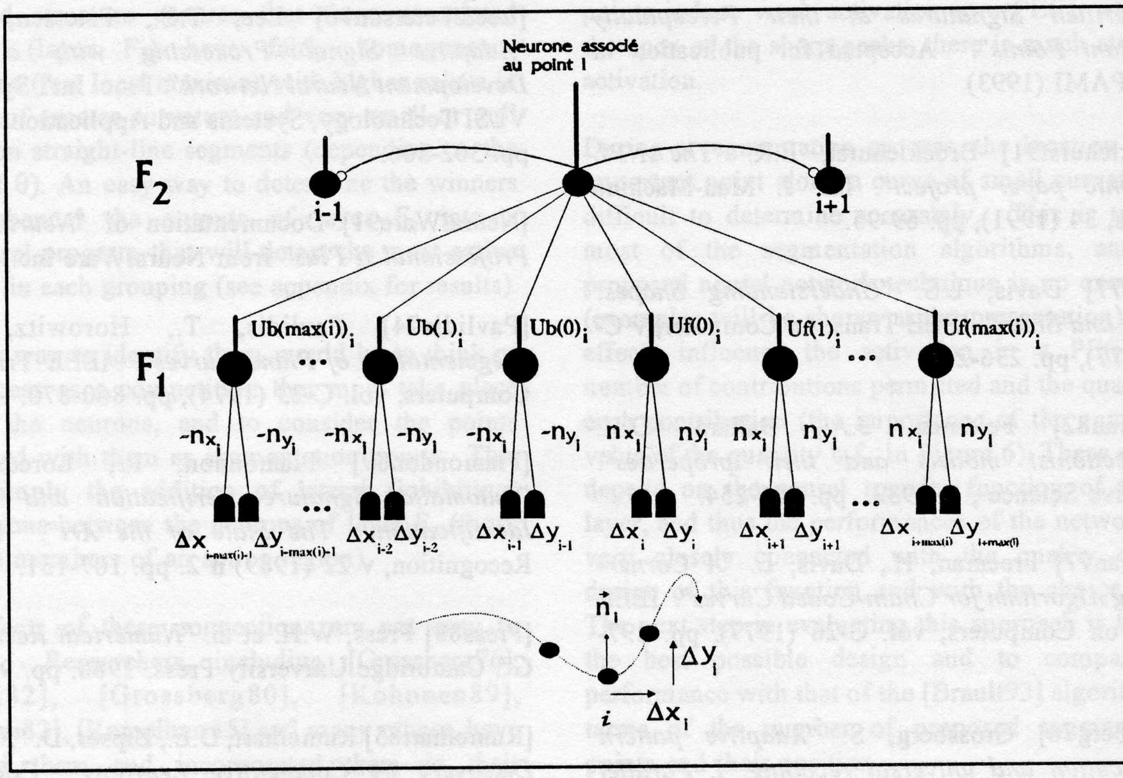

Figure 5 Structure of the net

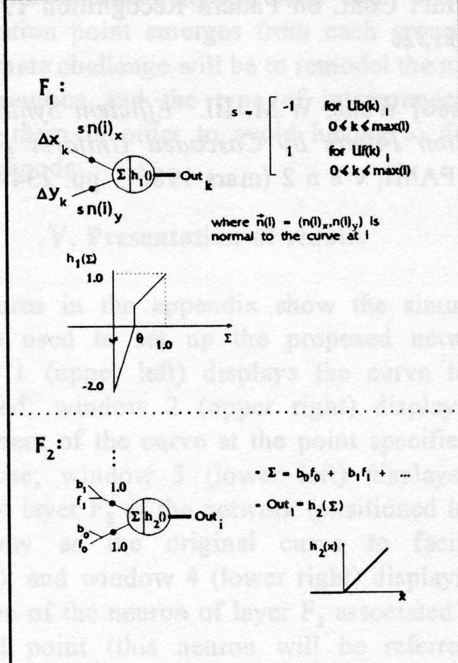

Figure 6 Definitions of neurons, connections, transfert functions

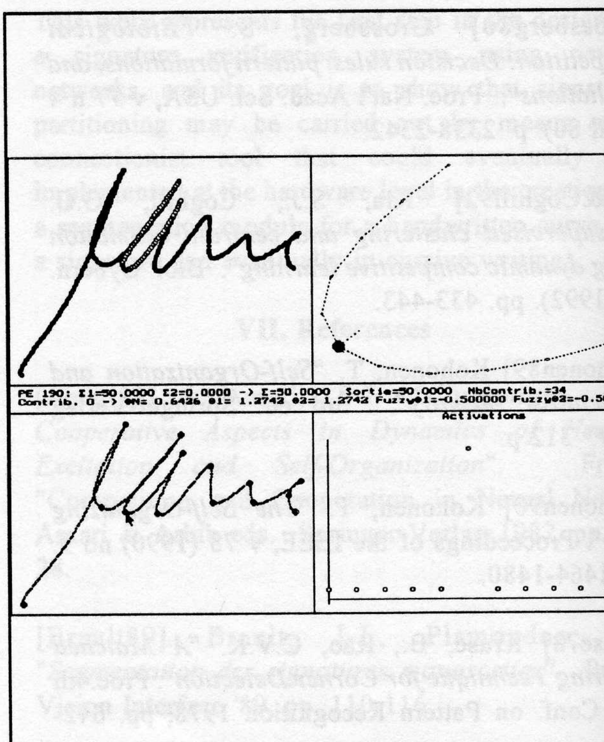

Figure 7 Example - partitioning of "Marc"