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The Method of Probabilistic Nodes Combination in Simulation and Modeling

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Abstract

Proposed approach, referred to as Probabilistic Nodes Combination (PNC), is the approach of 2D curve modeling and handwriting identity through the use of the set of key factors. Nodes are handled as function factors of signature or handwriting for modeling and creator recognition. Identification of handwritten letters or symbols want modeling and the version of every person image or person is constructed through a preference of opportunity distribution feature and nodes aggregate. PNC modeling thru nodes aggregate and parameter γ as opportunity distribution feature allows curve parameterization and interpolation for every particular letter or image. Two-dimensional curve is modeled and interpolated thru nodes aggregate and exclusive features as non-stop opportunity distribution features: polynomial, sine, cosine, tangent, cotangent, logarithm, exponent, arc sin, arc cos, arc tan, arc cot or electricity feature.

Keywords: handwriting identification, shape modeling, curve interpolation, PNC method, nodes combination, probabilistic modeling

INTRODUCTION

Handwriting identity and author verification are nonetheless the open questions in synthetic intelligence and laptop vision. Handwriting primarily based totally creator reputation gives a large wide variety of substantial implementations which make it an essential studies region in sample reputation [1]. There are such a lot of opportunities and programs of the popularity algorithms that carried out techniques ought to be worried on a unmarried hassle. Handwriting and signature identity represents this kind of substantial hassle. In the case of author reputation, defined on this paper, everyone is represented via way of means of the set of modeled letters or symbols. The caricature of proposed approach includes 3 steps: first handwritten letter or images have to be modeled via way of means of a curve, then in comparison with unknown letter and subsequently there's a selection of identity. Author reputation of handwriting and signature is primarily based totally on the selection of key factors and curve modeling. Reconstructed curve does now no longer ought to be clean withinside the nodes due to the fact a author does now no longer reflect on consideration on smoothing all through the handwriting. Curve interpolation in handwriting identity isn't best a natural mathematical hassle however essential undertaking in sample reputation and synthetic intelligence such as: biometric reputation [2-4], personalised handwriting reputation [5], automated forensic report examination [6,7], type of historic manuscripts [8]. Also author reputation in monolingual handwritten texts is an in depth region of look at and the techniques impartial from the language are well-seen. Proposed approach represents language-impartial and text-impartial method as it identifies the writer thru a unmarried letter or image from the sample. This novel approach is likewise relevant to quick handwritten text.

Writer reputation techniques withinside the current years are going to numerous directions: author reputation the use of multi-script handwritten texts [9], creation of latest functions [10], combining distinctive sorts of functions [3], analyzing the sensitivity of person length on author identity [11], investigating author identity in multi-script environments [9], effect of ruling strains on author identity [12], version perturbed handwriting [13], techniques primarily based totally on run-period functions [14,3], the edge-path and edge-hinge functions [2], a aggregate of codebook and visible functions extracted from chain code and polygonized illustration of contours [15], the autoregressive coefficients [9], codebook and green code extraction techniques [16], texture evaluation with Gabor filters and extracting functions [17], the use of Hidden Markov

Model [18-20] or Gaussian Mixture Model [1]. But no approach is managing author identity thru curve modeling or interpolation and factors evaluating as it's miles supplied on this paper.

The creator desires to method a hassle of curve interpolation [21-23] and form modeling [24] via way of means of feature factors in handwriting identity. Proposed approach is predicated on nodes aggregate and useful modeling of curve factors located among the primary set of key factors. The capabilities which are utilized in calculations constitute entire own circle of relatives of standard capabilities with inverse capabilities: polynomials, trigonometric, cyclometric, logarithmic, exponential and strength feature. These capabilities are handled as possibility distribution capabilities withinside the range [0;1]. Nowadays techniques observe particularly polynomial capabilities, for instance Bernstein polynomials in Bezier curves, splines and NURBS [25]. But Bezier curves do now no longer constitute the interpolation approach and cannot be used for instance in signature and handwriting modeling with feature factors (nodes). Numerical techniques for information interpolation are primarily based totally on polynomial or trigonometric capabilities, for instance Lagrange, Newton, Aitken and Hermite techniques. These techniques have a few vulnerable sides [26] and aren't enough for curve interpolation withinside the conditions whilst the curve cannot be construct via way of means of polynomials or trigonometric capabilities. Proposed 2D curve interpolation is the useful modeling thru any standard capabilities and it allows us to match the curve all through handwriting identity.

This paper offers novel Probabilistic Nodes Combination (PNC) approach of curve interpolation and takes up PNC approach of -dimensional curve modeling via the examples the use of the very very own circle of relatives of Hurwitz-Radon matrices (MHR approach) [27], but no longer exceptional (notable nodes combinations). The technique of PNC requires minimal assumptions: the exceptional facts about a curve is the set of at least nodes. Proposed PNC technique is applied in handwriting identification through first rate coefficients: polynomial, sinusoidal, cosinusoidal, tangent, cotangent, logarithmic, exponential, arc sin, arc cos, arc tan, arc cot or strength. Function for PNC calculations is chosen in my view at each modeling and it represents opportunity distribution feature of parameter α □ [0;1] for everything positioned among successive interpolation knots. PNC approach makes use of nodes of the curve pi = (xi,yi) Î R2, i = 1,2,…n:

1. PNC desires 2 knots or extra (n ≥ 2);
2. If first node and remaining node are the same (p1 = pn), then curve is closed (contour);
3. For extra particular modeling knots need to be settled at key factors of the curve, for instance neighborhood minimal or most and at the least one node among successive neighborhood extrema.

Condition 3 approach for example the first-rate issue of the curve in a particular orientation, convexity changing or curvature extrema. The purpose of this paper is to answer the question: the manner to model a handwritten letter or picture through manner of method of a difficult and rapid of knots [28]?

Probabilistic Interpolation

The technique of PNC is computing factors among successive nodes of the curve: calculated factors are interpolated and parameterized for actual number □ □ [0;1] withinside the variety of successive nodes. PNC technique makes use of the mixtures of nodes $p_1=(x_1,y_1)$, $p_2=(x_2,y_2)$,…, $p_n=(x_n,y_n)$ as $h(p_1,p_2,\ldots,p_m)$ and $m = 1,2,\ldots n$ to interpolate second coordinate y for first coordinate $c = \alpha\cdot x_i + (1-\alpha)\cdot x_{i+1}$, $i = 1,2,\ldots n-1$:

$$y(c) = \gamma \cdot y_i + (1-\gamma) y_{i+1} + \gamma(1-\gamma)\cdot h(p_1, p_2, \ldots, p_m), \qquad \textbf{(1)}$$

$\alpha \in [0;1]$, $\gamma = F(\alpha) \in [0;1]$.

Here are the examples of h computed for MHR method [29]:

$$h(p_1, p_2) = \frac{y_1}{x_1} x_2 + \frac{y_2}{x_2} x_1 \qquad \textbf{(2)}$$

or

$$h(p_1, p_2, p_3, p_4) = \frac{1}{x_1^2 + x_3^2}(x_1x_2y_1 + x_2x_3y_3 + x_3x_4y_1 - x_1x_4y_3) + \\ + \frac{1}{x_2^2 + x_4^2}(x_1x_2y_2 + x_1x_4y_4 + x_3x_4y_2 - x_2x_3y_4).$$

The examples of other nodes combinations:

$$h(p_1, p_2) = \frac{y_1x_2}{x_1y_2} + \frac{y_2x_1}{x_2y_1}$$

or

$$h(p_1, p_2) = \frac{y_1x_2}{y_2} + \frac{y_2x_1}{y_1}$$

or

$h(p_1, p_2) = x_1y_1 + x_2y_2$

or

$h(p_1, p_2) = x_1x_2 + y_1y_2$

or

$h(p_1, p_2,..., p_m) = 0$

or

$h(p_1) = x_1y_1$

or others. Nodes combination is chosen individually for each curve. Formula (1) represents curve parameterization as $\alpha \in [0;1]$:

$x(\alpha) = \alpha \cdot x_i + (1-\alpha) \cdot x_{i+1}$

and

$y(\alpha) = F(\alpha) \cdot y_i + (1 - F(\alpha))y_{i+1} + F(\alpha)(1 - F(\alpha)) \cdot h(p_1, p_2,..., p_m)$,

$y(\alpha) = F(\alpha) \cdot (y_i - y_{i+1} + (1 - F(\alpha)) \cdot h(p_1, p_2,..., p_m)) + y_{i+1}$.

Proposed parameterization gives us the endless style of possibilities for curve calculations (determined with the resource of the use of desire of F and h) as there can be the endless style of human signatures, handwritten letters and symbols. Nodes aggregate is the individual feature of each modeled curve (for example a handwritten letter or signature). Coefficient $\gamma = F(\alpha)$ and nodes aggregate h are key factors in PNC curve interpolation and shape modeling.

Interpolating functions in PNC modeling

Points settled between the nodes are computed using PNC method. Each real number $c \in [a;b]$ is calculated by a convex combination $c = \alpha \cdot a + (1 - \alpha) \cdot b$ for

$$\alpha = \frac{b-c}{b-a} \in [0;1].$$

Key query is managing coefficient γ in (1). The only manner of PNC calculation way h = zero and $\gamma = \alpha$ (simple opportunity distribution). Then PNC represents a linear interpolation. MHR method [30] isn't always a linear interpolation. MHR [31] is the instance of PNC modeling. Each interpolation calls for particular distribution of parameter α and γ (1) relies upon on parameter α □ [0;1]:

$\gamma = F(\alpha)$, $F:[0;1]\rightarrow[0;1]$, $F(0) = 0$, $F(1) = 1$

And F is precisely monotonic. Coefficient γ is calculated the usage of distinct features (polynomials, strength features, sine, cosine, tangent, cotangent, logarithm, exponent, arc sin, arc cos, arc tan or arc cot, additionally inverse features) and preference of characteristic is hooked up with preliminary necessities and curve specifications. Different values of coefficient γ are linked with carried out features $F(\alpha)$. These features $\gamma = F(\alpha)$ constitute the examples of opportunity distribution features for random variable α□[0;1] and actual wide variety s > 0:

$\gamma=\alpha^s$, $\gamma=sin(\alpha^s\cdot\pi/2)$, $\gamma=sin^s(\alpha\cdot\pi/2)$, $\gamma=1-cos(\alpha^s\cdot\pi/2)$, $\gamma=1-cos^s(\alpha\cdot\pi/2)$, $\gamma=tan(\alpha^s\cdot\pi/4)$, $\gamma=tan^s(\alpha\cdot\pi/4)$, $\gamma=log_2(\alpha^s+1)$, $\gamma=log_2{}^s(\alpha+1)$, $\gamma=(2^\alpha-1)^s$, $\gamma=2/\pi\cdot arcsin(\alpha^s)$, $\gamma=(2/\pi\cdot arcsin\alpha)^s$, $\gamma=1-2/\pi\cdot arccos(\alpha^s)$, $\gamma=1-(2/\pi\cdot arccos\alpha)^s$, $\gamma=4/\pi\cdot arctan(\alpha^s)$, $\gamma=(4/\pi\cdot arctan\alpha)^s$, $\gamma=ctg(\pi/2-\alpha^s\cdot\pi/4)$, $\gamma=ctg^s(\pi/2-\alpha\cdot\pi/4)$, $\gamma=2-4/\pi\cdot arcctg(\alpha^s)$, $\gamma=(2-4/\pi\cdot arcctg\alpha)^s$.

Functions above, utilized in γ calculations, are strictly monotonic for random variable α□[0;1] as $\gamma = F(\alpha)$ is chance distribution feature. Also inverse features $F\text{-}1(\alpha)$ are suitable for γ calculations. Choice of feature and price s relies upon on curve specs and man or woman requirements. Considering in recent times used chance distribution features for random variable α□[0;1] - one distribution is managing the range [0;1]: beta distribution. Probability density feature f for random variable $\alpha\in[0;1]$ is:

$$f(\alpha) = c \cdot \alpha^s \cdot (1-\alpha)^r \ , s \geq 0, r \geq 0. \qquad \textbf{(3)}$$

When $r = 0$ probability density function (3) represents $f(\alpha) = c \cdot \alpha^s$ and then probability distribution function F is like $f(\alpha) = 3\alpha^2$ and $\gamma = \alpha^3$. If s and r are positive integer numbers then γ is the polynomial, for example $f(\alpha) = 6\alpha(1-\alpha)$ and $\gamma = 3\alpha^2-2\alpha^3$. Beta distribution gives us coefficient γ in (1) as polynomial because of interdependence between probability density f and distribution F functions:

$$f(\alpha) = F'(\alpha) \ , \ F(\alpha) = \int_0^\alpha f(t)dt \cdot \qquad \textbf{(4)}$$

For example (4): $f(\alpha) = \alpha \cdot e^\alpha$ and $\gamma = F(\alpha) = (\alpha - 1)e^\alpha + 1$.

What could be very critical in PNC method: curves (as an example a handwritten letter or signature) may also have the equal set of nodes however one-of-a-kind h or γ outcomes in one-of-a-kind interpolations (Fig.6-14).
Algorithm of PNC interpolation and modeling (1) looks as follows:

Step 1: Choice of knots p_i at key points.
Step 2: Choice of nodes combination $h(p_1,p_2,\ldots,p_m)$.
Step 3: Choice of distribution $\gamma = F(\alpha)$.
Step 4: Determining values of α: α = 0.1, 0.2…0.9 (nine points) or 0.01, 0.02…0.99 (99 points) or others.
Step 5: The computations (1).
These 5 steps may be handled because the set of rules of PNC technique of curve modeling and interpolation (1).
Curve interpolation has to put in force the coefficients γ. Each strictly monotonic characteristic F among points (0;0) and (1;1) may be utilized in PNC interpolation.

Handwriting Modeling and Recognition

PNC approach permits signature and handwriting popularity. This technique of popularity includes 3 parts:
Modeling – desire of nodes aggregate and probabilistic distribution function (1) for recognized signature or handwritten letters;
Unknown writer - desire of feature factors (nodes) for unknown signature or handwritten phrase and the coefficients of factors among nodes;
Decision of popularity - evaluating the effects of PNC interpolation for recognized fashions with coordinates of unknown text.

Modeling – the basis of patterns

Known letters or symbols need to be modeled through the selection of nodes, figuring out unique nodes mixture and characteristic probabilistic distribution characteristic. For instance a handwritten phrase or signature "rw" might also additionally moreover furthermore appearance particular for folks A, B or others. How to version "rw" for a few dad and mom through PNC method? Each version have to be defined through the set of nodes for letters "r" and "w", nodes mixture h and a characteristic γ=F(α) for every letter. Less complex fashions can take h (p1,p2,…,pm) = zero after which the formulation of interpolation (1) appears as follows: $y(c) = \gamma \cdot y_i + (1-\gamma)y_{i+1}$.

It is linear interpolation for fundamental chance distribution (γ = α). How first letter "r" is modeled in 3 variations for nodes mixture h = 0 and α=zero.1,0.2…0.9? Of direction α is a random variable & α□[0;1].

Person A

Nodes (1;3), (3;1), (5;3), (7;3) and $\gamma = F(\alpha) = \alpha^2$:

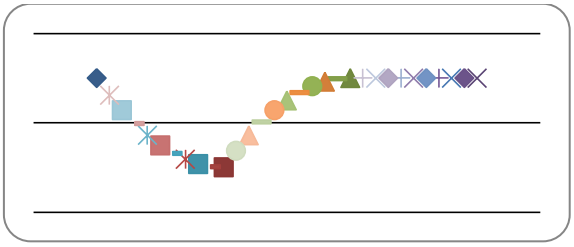

Fig. 1. PNC modeling for nine reconstructed points between nodes.

Person B

Nodes (1;3), (3;1), (5;3), (7;2) and $\gamma = F(\alpha) = \alpha^2$:

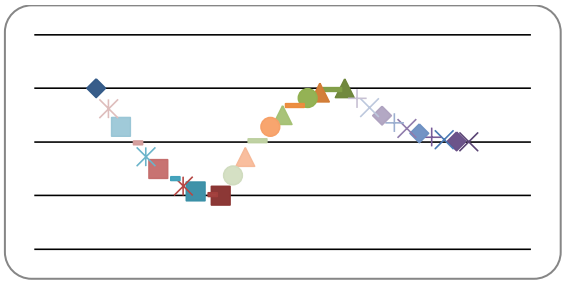

Fig. 2. PNC modeling of letter "*r*" with four nodes.

Person C

Nodes (1;3), (3;1), (5;3), (7;4) and $\gamma = F(\alpha) = \alpha^3$:

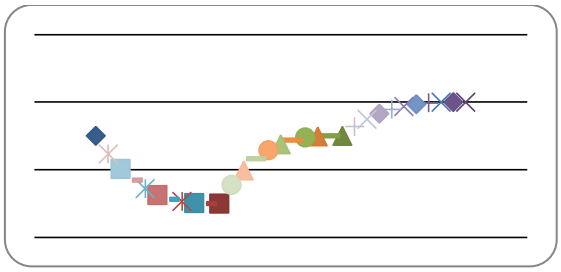

Fig. 3. PNC modeling of handwritten letter "*r*".

These 3 variations of letter "r" (Fig.1-3) with nodes mixture h = zero fluctuate at fourth node and opportunity distribution functions $\gamma = F(\alpha)$. Much greater opportunities of modeling are linked with a preference of nodes mixture h(p1,p2,…,pm). MHR method [32] makes use of the mixture (2) with proper functions due to orthogonal rows and columns at Hurwitz-Radon own circle of relatives of matrices:

$$h(p_i, p_{i+1}) = \frac{y_i}{x_i} x_{i+1} + \frac{y_{i+1}}{x_{i+1}} x_i$$

and then (1)

$$y(c) = \gamma \cdot y_i + (1-\gamma) y_{i+1} + \gamma(1-\gamma) \cdot h(p_i, p_{i+1},) \cdot$$

Here are two examples of PNC modeling with MHR combination (2).

Person D

Nodes (1;3), (3;1), (5;3) and $\gamma = F(\alpha) = \alpha^2$:

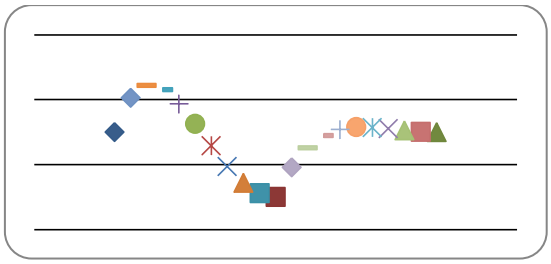

Fig. 4. PNC modeling of letter "*r*" with three nodes.

Person E

Nodes (1;3), (3;1), (5;3) and $\gamma = F(\alpha) = \alpha^{1.5}$:

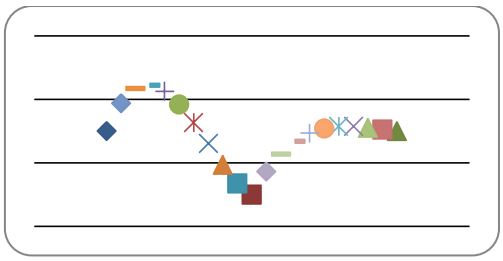

Fig. 5. PNC modeling of handwritten letter "*r*".

Fig.1-5 show modeling of letter "*r*". Now let us consider a letter "*w*" with nodes combination $h = 0$.

Person A

Nodes (2;2), (3;1), (4;2), (5;1), (6;2) and $\gamma = F(\alpha) = (5^{\alpha} - 1)/4$:

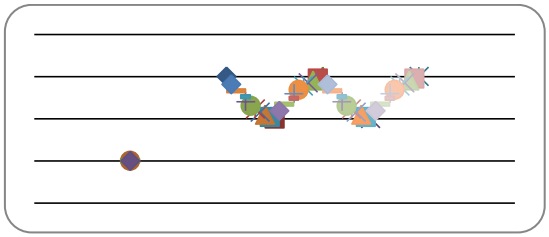

Fig. 6. PNC modeling for nine reconstructed points between nodes.

Person B

Nodes (2;2), (3;1), (4;2), (5;1), (6;2) and $\gamma = F(\alpha) = sin(\alpha \cdot \pi/2)$:

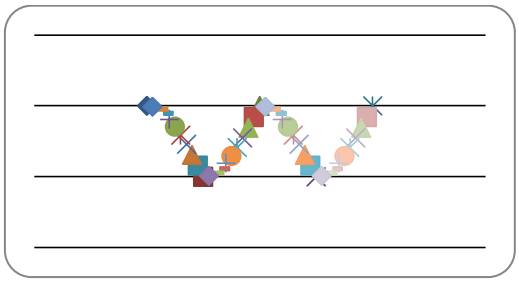

Fig. 7. PNC modeling of letter "*w*" with five nodes.

Person C

Nodes (2;2), (3;1), (4;2), (5;1), (6;2) and $\gamma = F(\alpha) = sin^{3.5}(\alpha \cdot \pi/2)$:

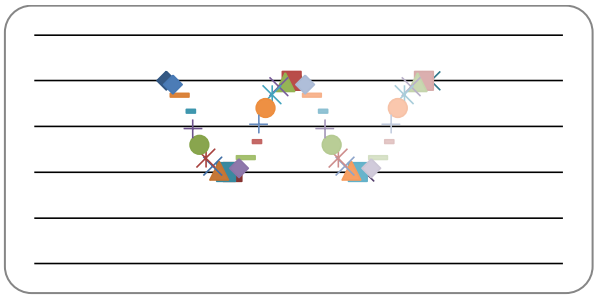

Fig. 8. PNC modeling of handwritten letter "*w*".

These 3 variations of letter "w" (Fig.6-8) with nodes mixture h = zero and the equal nodes range most effective at chance distribution capabilities $\gamma = F(\alpha)$. Fig.nine is the instance of nodes mixture h (2) from MHR method:

Person D

Nodes (2;2), (3;1), (4;1), (5;1), (6;2) and $\gamma = F(\alpha) = 2^{\alpha} - 1$:

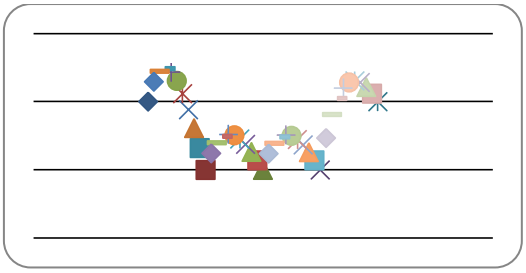

Fig. 9. PNC modeling for nine reconstructed points between nodes.

Examples above have one characteristic γ = F(α) and one mixture h for all degrees among nodes. But it's far viable to create a version with capabilities γi = Fi(α) and mixtures hello for my part for a number of nodes (pi;pi+1). It permits very specific modeling of handwritten image among every successive pair of nodes.

Each person has its own characteristic and individual handwritten letters, numbers or other marks. The variety of coefficients x must be the equal for all fashions due to evaluating suitable coordinates y. Every letter is modeled with the aid of using PNC thru 3 elements: the set of nodes, possibility distribution characteristic γ = F(α) and nodes aggregate h. These 3 elements are selected in my opinion for every letter, consequently this statistics approximately modeled letters appears to be sufficient for particular PNC curve interpolation, evaluating and handwriting identification. Function γ is chosen thru the evaluation of factors among nodes and we can also additionally count on h = zero on the beginning. What may be very important - PNC modeling is impartial of the language or a sort of symbol (letters, numbers or others). One man or woman can also additionally have numerous styles for one handwritten letter. Summarize: every person has the basis of patterns for each handwritten letter or symbol, described by the set of nodes, probability distribution function γ = $F(\alpha)$ and nodes combination h. Whole basis of patterns consists of models $\boldsymbol{S_j}$ for $j = 0,1,2,3\ldots K$.

Unknown author – points of handwritten character

Choice of characteristic points (nodes) for unknown letter or handwritten symbol is a crucial factor in object recognition. The variety of coefficients x must be the equal just like the x variety withinside the foundation of patterns. Knots of the curve (opened or closed) must be settled at key points, for instance nearby minimal or most (the very best factor of the curve in a specific orientation), convexity converting or curvature most and at the least one node among successive key points. When the nodes are fixed, every coordinate of each selected factor at the curve (x0c,y0c), (x1c,y1c),…, (xMc,yMc) is offered for use for evaluating with the models. Then chance distribution characteristic γ = F(α) and nodes aggregate h need to be taken from the idea of modeled letters to calculate suitable 2nd coordinates yi(j) of the sample Sj for first coordinates xic, i = 0,1,…,M. After interpolation it's miles viable to evaluate given handwritten image with a letter withinside the foundation of patterns.

Recognition – the writer

Comparing the results of PNC interpolation for required second coordinates of a model withinside the inspiration of patterns with elements on the curve (x0c,y0c), (x1c,y1c),…, (xMc,yMc), we can say if the letter or picture is written thru character A, B or another. The evaluation and choice of popularity [33] is accomplished thru minimum distance criterion. Curve factors of unknown handwritten image are: (x0c,y0c), (x1c,y1c),…, (xMc,yMc). The criterion of popularity for fashions Sj = , j=0,1,2,3…K is given as:

$$\sum_{i=0}^{M}\left|y_i^{\,c} - y_i^{\,(j)}\right| \to \min .$$

Minimal distance criterion enables us to restoration a candidate for unknown author as someone from the version Sj.

Conclusions

The approach of Probabilistic Nodes Combination (PNC) permits interpolation and modeling of -dimensional curves [34] using nodes combos and precise coefficients γ: polynomial, sinusoidal, cosinusoidal, tangent, cotangent, logarithmic, exponential, arc sin, arc cos, arc tan, arc cot or power function, moreover inverse capabilities. Function for γ calculations is chosen in my opinion at each curve modeling and it's miles treated as possibility distribution function: γ is based upon on initial requirements and curve specifications. PNC approach effects in curve interpolation as handwriting or signature identification thru discrete set of steady knots. PNC makes possible the mixture of crucial problems: interpolation and modeling in a depend of author identification. Main capabilities of PNC technique are:

a) The smaller distance among knots the better;

b) Calculations for coordinates near 0 and close to via way of means of extremum require greater interest due to significance of those factors;
c) PNC interpolation develops a linear interpolation into different capabilities as opportunity distribution capabilities;
d) PNC is a generalization of MHR technique through unique nodes mixtures;
e) Interpolation of L factors is hooked up with the computational fee of rank O(L) as in MHR technique;
f) Nodes aggregate and coefficient γ are important withinside the method of curve probabilistic parameterization and interpolation: they're computed for my part for a unmarried curve.

Future works are going to: software of PNC technique in signature and handwriting reputation, desire and capabilities of nodes mixtures and coefficient γ, implementation of PNC in laptop imaginative and prescient and synthetic intelligence: form geometry, contour modelling, item reputation and curve parameterization.

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