Concentration of Oxygen Based on a Luminescent Sensitive Element /International conference ICISCT 2019, Tashkent 2019.
4. Balentine D. A., Wiseman S. A., Bouwens L. C. The Chemistry of Tea Flavonoids. *Crit. Rev. Food Sci. Nutr.* 1997, v. 37, p. 693-704.
5. Stensvold I., Tverdal A., Solvoll K., and Foss O. P. *Tea Consumption. Relationship to Cholesterol, Blood Pressure, and Coronary and Total Mortality.* Pvev. Med., 1992, v. 21, p. 546-553.
6. Sasazuki S., Kodama H., Yoshimasu K., et al. *Relation between Green Tea Consumption and the Severity of Coronary Atherosclerosis among Japanese Men and Women.* Ann. Epidemiol., 2000, v. 10, p. 401-408.
7. Riemersma R. A., Rice-Evans C. A., Tyrrell R. M., Clifford M. N. and Lean M. E. *Tea Flavonoids and Cardiovascular Health.* Q.J.M., 2001, v. 94, p. 277-282.
8. Imai K., Suga K., and Nakachi K. *Cancer- Preventive Effects of Drinking Green Tea Among a Japanese Population.* Prev. Med., 1997, v. 26, p. 769-775.
9. Liu Z., Ma L. P. , Zhou B., Yang L., and Liu Z. L. *Antioxidative Effects of Green Tea Polyphenols on Free Radical Initiated and Photosensitized Peroxidation of Human Low Density Lipoprotein.* Chem. Phys. Lipids, 2000, v. 106, p. 53-63.

NON-DEPENDENT CUBIC SPLINE FUNCTION AND ITS USE IN DIGITAL PROCESSING OF SIGNS

H.N.Zaynidinov[1][0000-0002-8098-5246], S.A.Bakhromov[2][0000-0002-5797-9577], B.R.Azimov[3][0000-0002-6919-7505], N.H.Sadritdinov[4][0000-0002-2253-3233]

[1]*Tashkent University of Information Technologies, 100200, Tashkent city, Republic of Uzbekistan*
Tet2001@rambler.ru
[2]*National University of Uzbekistan, 100174, Tashkent city, Republic of Uzbekistan*
baxromov59@mail.ru
[3]*Andijan State University, 170100, Andijan city, Republic of Uzbekistan*
bunyodbekazimov@mail.ru
[4]*Tashkent State Technical University, 100095, Tashkent city, Republic of Uzbekistan*
nizomiddin.sadritdinov@bk.ru

Abstract. *This paper proposes a method of constructing cubic spline functions of a local character with equal distances between nodes. Previous studies have shown precise models for the digital processing of signals using interpolated cubic splines, with accurate examples showing the high degree of accuracy of the approximation of interpolated functions. In this study, the size of the calculations required to find the parameters to be determined during the construction of the spline function does not depend on the number of node points. Local-based splines are used to build such spline functions. Digital processing of the gastroenterological signal was performed on the basis of the spline-function model discussed in the article.*

Keywords. *Gastroentrological signal, spline-function, interpolation cubic spline, interpolation, cubic spline independent of node points.*

Introduction

Today, spline-function models are widely used by researchers in the field of digital signal processing [1, 2]. Because the accuracy of spline functions is higher than that of classical polynomials, and the algorithms based on them require less computation. Existing classical interpolation models, their application in signal recovery and digital processing algorithms are performed depending on the node points. In this case, a large number of node points are required for these models to have a high degree of convergence. In cases where the nodes are point-dependent, the order of the system of equations formed in the construction of the model under consideration increases. And this complicates the process of solving a system of equations and does not ensure a high level of accuracy of the model [3, 4, 14-20].

The process of digital processing of signals of the spline model discussed in this article was carried out independently of the node points. In this case, the increase in the degree of convergence of the model under consideration does not depend on the increase in the order of the system of equations. Methods for determining nonlinear spline functions, their derivatives, and estimating errors are performed in the same way as for simple interpolation splines [5, 9,10].

2. Local base functions

Let us be given the following function [12].

$$G(x,t)=(x-t)^3=\begin{cases}(x-t)^3, & x\ge t\\ 0, & x<t\end{cases} \tag{1}$$

Assume that the $\{x_i\}$ node points on the OX axis are defined in steps h as follows.

$x_{i+1}=x_i+h,\ i=1,2,...,M$, $G(x,t)$ we enter the fourth-order divisor of the function separately for the $x_{i-2},x_{i-1},x_i,x_{i+1},x_{i+2}$ node points on the variable i:

$$\varphi_i(x)=G(x_{i-2},x_{i-1},x_i,x_{i+1},x_{i+2}),$$
$$i=3,4,\ldots,M-2$$

The fourth-order difference of the $\varphi(x)$ function is determined by the following formula:

$$f(x_{i-2},x_{i-1},x_i,x_{i+1},x_{i+2})=$$
$$=\frac{f(x_{i-1},x_i,x_{i+1},x_{i+2})-f(x_{i-2},x_{i-1},x_i,x_{i+1})}{x_{i-2}-x_{i+2}}.$$

In turn, $x_{i-1},x_i,x_{i+1},x_{i+2}$ and $x_{i-2},x_{i-1},x_i,x_{i+1}$ are also calculated sequentially as above.

After some simplification, the calculation formula for the fourth-order subtraction difference of the $G(x,t)$ function will look like this:

$$\varphi_i(x)=G(x_{i-2},x_{i-1},x_i,x_{i+1},x_{i+2})=$$
$$\frac{1}{4!h^4}[(x-x_{i+2})_+^3-4(x-x_{i+1})_+^3$$
$$+6(x-x_i)_+^3-4(x-x_{i-1})_+^3+(x-x_{i-2})_+^3] \tag{2}$$

Based on the features discussed above, the following forms the basis in the space of tertiary splines

$$S_i(x)=\frac{\varphi_i(x)}{\varphi_i(x_i)},\quad i=3,4,5,\ldots,M-2 \tag{3}$$

Let's look at the features.

This function forms the basis in the space of cubic splines and has the following features:

1) Smoothness

$$S_i(x)\in C^2[x_1,x_M] \tag{3^1}$$

2) Locality

$$S_i(x)>0,\ \ x\in(x_{i-2},x_{i+2})$$
$$S_i(x)\equiv 0,\quad x\notin(x_{i-2},x_{i+2}),$$
$$i=3,4,5\ldots,\quad M-2 \tag{3^2}$$

Here we see as proof

$\varphi_i(x)=0$ if $x\notin(x_{i-2},x_{i+2})$

Now let's calculate $\varphi_i(x_{i-2})$, $\varphi_i(x_{i-1})$, $\varphi_i(x_i)$, $\varphi_i(x_{i+1})$ *and* $\varphi_i(x_{i+2})$:

$$\varphi_i(x_{i-2})=\frac{1}{4!h_i^4}\Big[(x_{i-2}-x_{i+2})_+^3-4(x_{i-2}-x_{i+1})_+^3+6(x_{i-2}-x_i)_+^3$$
$$-4(x_{i-2}-x_{i-1})_+^3+(x_{i-2}-x_{i-2})_+^3\Big]=\left\{G(x,t)=(x-t)_-^3=\begin{Bmatrix}(x-t)^3, & x\ge t\\ 0, & x>t\end{Bmatrix}=0\right.$$

$$\varphi_i(x_{i-2}) = (4h)^3 - 4(3h)^3 + 6(2h)^3 - 4h^3 = 64h^3 - 108h^3 + 48h^3 - 4h^3 = 0$$

$$\varphi_i(x_{i-2}) = 0 \tag{4}$$

The rest according to (3^2) are also found as follows

$$\varphi_i(x_{i-1}) = \frac{1}{24h} \tag{5}$$

$$\varphi_i(x_i) = \frac{1}{6h} \tag{6}$$

$$\varphi_i(x_{i+1}) = \frac{1}{24h} \tag{7}$$

$$\varphi_i(x_{i+2}) = 0 \tag{8}$$

As above, we find

$$\varphi_i(x_{i-2}), \varphi_i(x_{i-1}), \varphi_i(x_i), \varphi_i(x_{i+1}), \varphi_i(x_{i+2})$$

based on the following nodes.

That is:

$$\varphi_{i-2}(x): \quad x_{i-4},\ i-3,\ i-2,\ i-1,\ i$$

$$\varphi_{i-1}(x): \quad i-3,\ i-2,\ i-1,\ i,\ i+1$$

$$\varphi_i(x): \quad i-2,\ i-1,\ i,\ i+1,\ i+2$$

$$\varphi_{i+1}(x): \quad i-1,\ i,\ i+1,\ i+2,\ i+3$$

$$\varphi_{i+2}(x): \quad i,\ i+1,\ i+2,\ i+3,\ i+4$$

$$\varphi_{i-2}(x) = G(x, x_{i-4}, x_{i-3}, x_{i-2}, x_{i-1}, x_i) = \frac{1}{4!h^4}[(x-x_i)_+^3 - 4(x-x_{i-1})_+^3 +$$

$$+6(x-x_{i-2})_+^3 - 4(x-x_{i-3})_+^3 + (x-x_{i-4})_+^3] = \frac{1}{4!h^4}[C_4^0(x-x_i)_+^3 - C_4^1(x-x_{i-1})_+^3 + C_4^2(x-x_{i-2})_+^3 -$$

$$-C_4^3(x-x_{i-3})_+^3 + C_4^4(x-x_{i-4})_+^3] = \frac{1}{4!h^4}\sum_{j=-4}^{0}(-1)^{4+j}C_4^{4+j}(x-x_{i+j})_+^3$$

We perform the $x_i < x < x_{i+1}$, $t = \frac{x - x_i}{h}$ replacement as follows, which will be $x_{i+j} = h(t-j)$.

In that case

$$\varphi_{i-2}(x)=\frac{1}{4!h^4}\sum_{j=-4}^{0}(-1)^{4+j}*C_4^{4+j}\left(\frac{x-x_i+x_i-x_{i-4-j}}{h}\right)h^3=$$

$$=\frac{1}{4!h}\sum_{j=-4}^{0}(-1)^{4+j}C_4^{4+j}[t+(j+4)]^3=$$

$$=\frac{1}{24h}[(-1)^0C_4^0[t+0]^3+(-1)^1C_4^1[t+1]^3+(-1)^2C_4^2[t+2]^3+(-1)^3C_4^3[t+3]^3+$$

$$(-1)^4C_4^4[t+4]^3]=\frac{1}{24h}[t^3-4(t+1)^3+6(t+2)^3-4(t+3)^3+(t+4)^3]=$$

$$=\frac{1}{24h}[t^3-4t^3-12t^2-12t-4+6t^3+36t^2+72t+48-4t^3-36t^2-108t-$$

$$-108+t^3+12t^2+48t+64]=\frac{1}{24h}[(1-4+6-4+1)t^3+(-12+36-36+12)t^2+(-12+72-108+48)t+$$

$$+(-4+48-108+64)]=0$$

$$\varphi_{i-2}(x)=0$$

$$\varphi_{i+2}(x)=G(x,x_i,x_{i+1},x_{i+2},x_{i+3},x_{i+4})=\frac{1}{24h}[C_4^0[x-x_{i+4}]_+^3+C_4^1[x-x_{i+3}]_+^3+$$

$$C_4^2[x-x_{i+2}]_+^3+C_4^3[x-x_{i+1}]_+^3+C_4^4[x-x_{i+1}]_+^3]=\frac{1}{24h}(x-x_i)^3$$

Now let's do a $t=\frac{x-x_i}{h}$ switch at $x\in[x_i,x_{i+1}]$, it will be $x-x_{i+j}=h(t-j)$.

In that case

$$\varphi_{i+2}(x)=\frac{1}{24h}(\frac{x-x_i}{h}h)^3=\frac{1}{24h}h^3(\frac{x-x_i}{h})^3$$

$$\varphi_{i+2}(x)=\frac{1}{24h}t^3$$

based on the above, we also substitute the $\varphi_{i-1}(x),\varphi_i(x),\varphi_{i+1}(x)$ for the variable t to form the following

$$\varphi_{i-2}(x)=0 \tag{9}$$

$$\varphi_{i-1}(x)=\frac{1}{24h}(1-t)^3 \tag{10}$$

$$\varphi_i(x)=\frac{1}{24h}(3t^3-6t^2+4) \tag{11}$$

$$\varphi_{i+1}(x)=\frac{1}{24h}(1+3t+3t^2-3t^3) \tag{12}$$

$$\varphi_{i+2}(x)=\frac{1}{24h}t^3 \tag{13}$$

We create based on the following functions (3) that form the basis in the field of tertiary splines. We construct the basic functions based on (4) - (8) and (9) - (13).

$$S_{i-2}(x)=\frac{\varphi_{i-2}(x)}{\varphi_{i-2}(x_{i-2})}=0 \tag{14}$$

$$S_{i-1}(x)=\frac{\varphi_{i-1}(x)}{\varphi_{i-1}(x_{i-1})}=\frac{\frac{1}{24h}(1-t)^3}{\frac{1}{6h}}=\frac{1}{4}(1-t)^3 \tag{15}$$

$$S_i(x)=\frac{\varphi_i(x)}{\varphi_i(x_i)}=\frac{\frac{1}{24h}(3t^3-6t^2+4)}{\frac{1}{6h}}=$$
$$=\frac{1}{4}(3t^3-6t^2+4) \tag{16}$$

$$S_{i+1}(x)=\frac{\varphi_{i+1}(x)}{\varphi_{i+1}(x_{i+1})}=$$
$$=\frac{\frac{1}{24h}(1+3t+3t^2-3t^3)}{\frac{1}{6h}}=\frac{1}{4}(1+3t+3t^2-3t^3) \tag{17}$$

$$S_{i+2}(x)=\frac{\varphi_{i+2}(x)}{\varphi_{i+2}(x_{i+2})}=\frac{\frac{1}{24h}t^3}{\frac{1}{6h}}=\frac{1}{4}t^3 \tag{18}$$

The values of the $f(x)$ function at the $f_i=f(x_i),\ i=3,M-2$ node points are given $x_4=a, x_{M-3}=b$.

Consider the following function.

$$S(x)=\sum_{i=3}^{M-2} f_i S_i(x), \quad x\in(x_4,x_{M-3})$$

From this function

$$S_i(x)>0, \quad x\in(x_{i-2},x_{i+2})$$

$$S_i(x)\equiv 0, \quad x\notin(x_{i-2},x_{i+2})$$

the local condition is required.

In that case, the values at the node point of the $S_i(x)$ function based on the localization condition are as follows.

$$S(x_i)=\sum_{j=i-1}^{i+1} f_j S_j(x_i), \quad i=4,M-3$$

For simplicity

$$S(x_i)=\sum_{p=-1}^{1} f_{i+p} S_{i+p}(x_i)$$

That is

$$S(x_i)=f_{i-1}S_{i-1}(x_i)+f_iS_i(x_i)+$$
$$+f_{i+1}S_{i+1}(x_i),\qquad i=\overline{4,M-3}$$

The $S_i(x)$ function at values p= 0.1 is as follows

$$S_{i+p}(x_i)=S_{i-p}(x_i)=S_i(x_{i+p})=$$
$$=S_i(x_{i-p})=a_p$$

has properties

$$a_p=\begin{cases}1 & агар \quad p=0\\ 0{,}25 & агар \quad p=1\end{cases}$$

That is, at p = 0

$$S_i(x_i)=S_i(x_i)=S_i(x_i)=S_i(x_i)=1$$

really

$$S_i(x)=\frac{\varphi_i(x)}{\varphi_i(x_i)}\quad ,$$

in this

$$S_i(x_i)=\frac{\varphi_i(x_i)}{\varphi_i(x_i)}=1,$$

The case p = 1 is similar.

As a result

$$S(x_i)=0{,}25f_{i-1}+1f_i+0{,}25f_{i+1}=$$
$$=f+0{,}25(f_{i-1}+f_{i+1}),\ i=\overline{4,M-3}$$

We now express the f_{i-1}, f_{i+1} through the f_i, for which we spread them to the Taylor series

$$f_{i-1}=f_i+hf_i^{'}+\frac{h^2}{2}f_i^{''}$$

$$f_{i+1}=f_i-hf_i^{'}+\frac{h^2}{2}f_i^{''}$$

By adding these expressions we get the following

$$f_{i-1}+f_{i+1}=2f_i+\frac{h^2}{2}(f_i^{''}+f_i^{''})$$

$$f_{i-1}+f_{i+1}=2f_i+O(h^2)$$

$$0{,}25(f_{i-1}+f_{i+1})=0{,}5f_i+O(h^2)$$

In that case

$$S(x_i)=f_i+\frac{1}{4}(f_{i-1}+f_{i+1})=f_i+\frac{1}{2}f_i+O(h^2)\ ,$$

From this

$$S(x_i)=\frac{3}{2}f_i+O(h^2)$$

We will have $S(x_i)=\frac{3}{2}f_i+O(h^2)$.

The smoother the $f(x)$ function, the closer it is to f_i in $(f_{i-1}+f_{i+1})/2$ calculations.

And the $S_i(x)$ spline function is close to the $k\frac{3}{2}f(x)$ at the node points then we find the next approximate function

$$S^*(x_i)=\frac{2}{3}S(x_i)=\frac{2}{3}[\frac{3}{2}f_i+O(h^2)]$$

$$S^*(x_i)=f_i+O(h^2)$$

in which case it can be obtained

$$S^*(x)=\frac{2}{3}\sum_{i=3}^{M-2} f_i S_i(x)$$

$$S^*(x)=\frac{2}{3}S_{i-1}(x)f_{i-1}+\frac{2}{3}S_i(x)f_i+$$
$$+\frac{2}{3}S_{i+1}(x)f_{i+1}+\frac{2}{3}S_{i+2}(x)f_{i+2}$$

We enter the following notation, where $t=\frac{x-x_i}{h}, x=x_i+th$,

$$\psi_1(t)=\frac{2}{3}S_{i-1}(x);\quad \psi_2(t)=\frac{2}{3}S_i(x);$$
$$\psi_3(t)=\frac{2}{3}S_{i+1}(x);\quad \psi_4(t)=\frac{2}{3}S_{i+2}(x)$$

In that case

$$S^*(x)=\psi_1(t)f_{i-1}+\psi_2(t)f_i+$$
$$+\psi_3(t)f_{i+1}+\psi_4(t)f_{i+2}$$

It is not difficult to calculate $\psi_i(t)$.

We will see one of them count

$$\psi_1(t)=\frac{2}{3}S_{i-1}(x)=\frac{2}{3}\frac{1}{4}(1-t)^3=\frac{1}{6}(1-t)^3$$

the rest are calculated similarly.

$$\psi_2(t)=\frac{1}{6}(3t^3-6t^2+4)$$

$$\psi_3(t)=\frac{1}{6}(1+3t+3t^2+3t^3)$$

$$\psi_4(t)=\frac{1}{6}t^3$$

As a result, we write the general view of a tertiary spline function that is independent of node points as follows

$$S^*(x)=\sum_{j=1}^{4}\psi_j(t)f_{i-2+j}$$

Here

$$\begin{cases}\psi_1(t)=\frac{1}{6}(1-t)^3\\ \psi_2(t)=\frac{1}{6}\left(3t^3-6t^2+4\right)\\ \psi_3(t)=\frac{1}{6}\left(1+3t+3t^2+3t^3\right)\\ \psi_4(t)=\frac{1}{6}t^3\end{cases}$$

3. Digital processing of gastroenterological signals based on developed algorithms.

The construction of cubic spline models was performed on the basis of the gastroenterological signal given in Table 1 as the initial data [3, 6, 7]. Based on the above sequence, a cubic spline construction program in the MATLAB software environment of the gastroenterological signal given in Table 1 was developed and used in the processing of the gastroenterological signal [8, 11, 13]. The algorithm of this program is shown in Figure2.

Table 1.

Values of gastroenterological signal.

№	X	Y	№	X	Y
1.	1	-5617	11.	11	1969
2.	2	-5726	12.	12	3099
3.	3	-5504	13.	13	4038
4.	4	-4968	14.	14	4734
5.	5	-4153	15.	15	5151
6.	6	-3112	16.	16	5268
7.	7	-1905	17.	17	5082
8.	8	-606	18.	18	4607
9.	9	710	19.	19	3873
10.	10	-5617	20.	20	2925

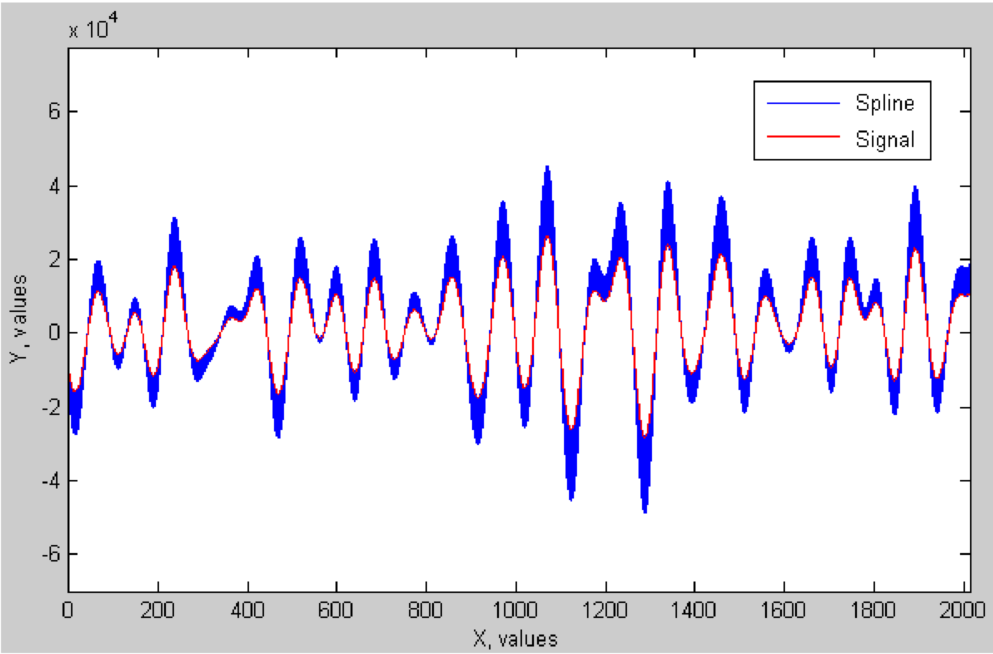

Fig. 1. ***Results of gastroenterological signal recovery.***

Table 2.

Error results in the process of digital processing of the gastroenterological signal.

№	Model types	Absolute error
1.	Lagrange classical interpolation model	1.0493
2.	A cubic spline model that does not depend on node points	0.1025

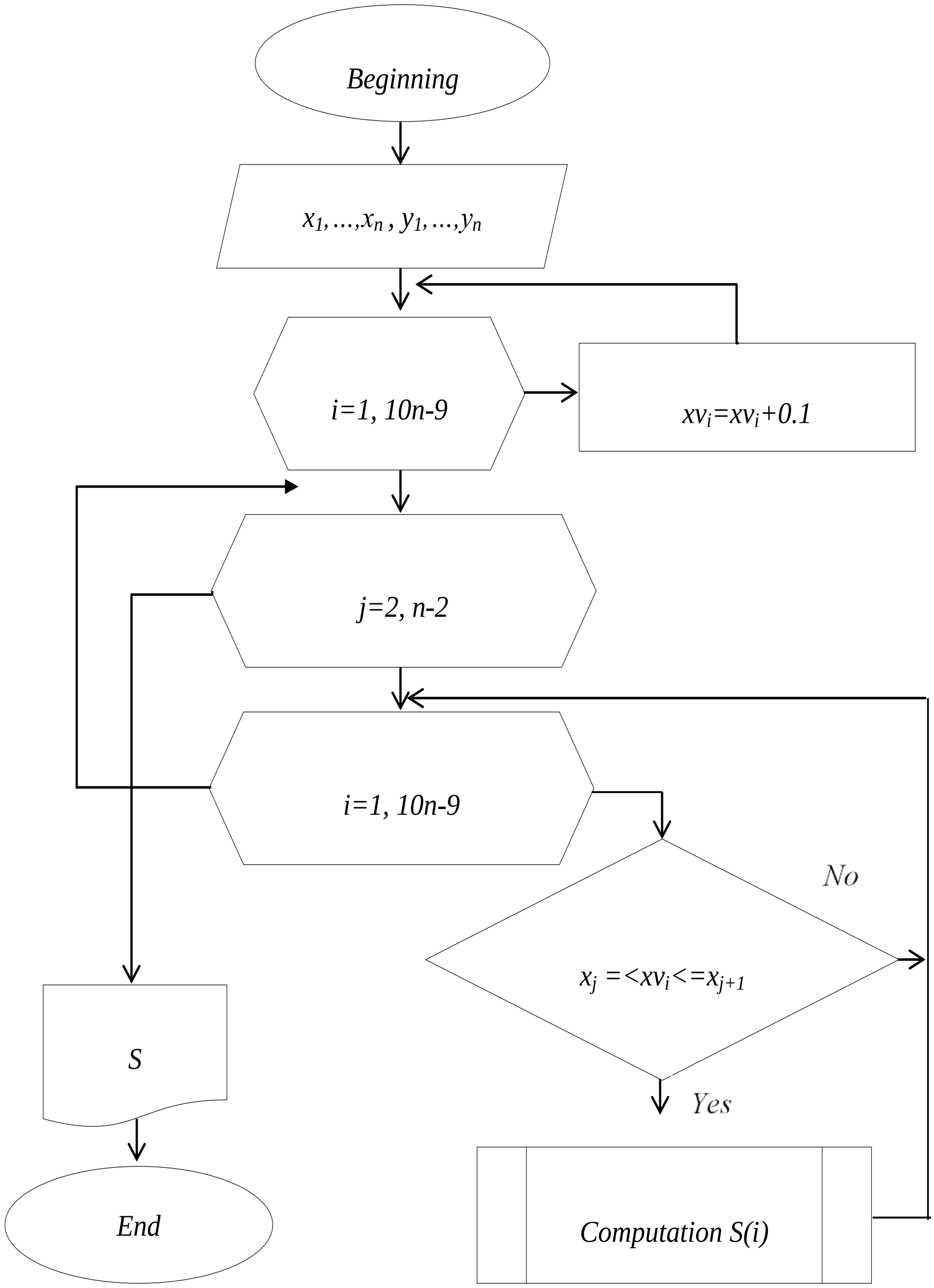

Fig. 2. ***Algorithm of cubic spline construction program.***

4. Conclusion

This paper proposes a method of constructing a tertiary spline model that is not dependent on node points in equally distributed networks using precise spline functions of a local character. And was used in the digital processing of the gastroenterological signal. The process of gastroenterological signal recovery was performed using the proposed method. The result showed that the method of tertiary spline functions independent of node points showed high accuracy in digital processing of signals (Figure 1).

The proposed cubic spline model has the following features compared to classical interpolation models:

-good proximity to the object when interpolating gastroentrological signals;

-the construction of the model is independent of node points and is much simpler than the classical polynomials;

-that the algorithm for determining the parameters of the spline is simple and convenient.

Hence, the use of cubic spline models built independently of the node points according to Table 2 gives good results in the digital processing of gastroenterological signals.

References

1. H. N. Zaynidinov, B.R. Azimov, “Biomedical signals interpolation spline models” in 2020 International conference on information science and communications technologies (ICISCT). https:/doi.org/10.1109/ICISCT47635.2019.9011926.
2. J. Rajeswari, M. Jagannath, “Advances in biomedical signal and image processing – A systematic review” IEEE Trans. 8, 13-19, 2017. https://doi.org/10.1016/j.imu.2017.04.002.
3. Abdulhamit Subasi. Practical Guide for Biomedical Signals Analysis Using Machine Learning Techniques A MATLAB® Based Approach, 2019.
4. S. Patidar, T. Panigrahi, “Detection of epileptic seizure using kraskov entropy applied on tunable-Q wavelet transform of EEG signals”, Biomed Signal Process Control, 34 (2017), pp. 74-80. https://doi.org/10.1016/j.bspc.2017.01.001.
5. M. Unser, "Splines: A Perfect Fit for Signal and Image Processing," IEEE Signal Processing Magazine, vol. 16, no. 6, pp. 22-38, 1999. https://doi.org/10.1109/79.799930.
6. Koredianto Usman, Mohammad Ramdhani. “Comparison of Classical Interpolation Methods and Compressive Sensing for Missing Data Reconstruction”, 2019 IEEE International Conference on Signals and Systems (ICSigSys). https://ieeexplore.ieee.org/document/8811057.
7. A.V. Shumilov. “Analysis of existing and development of new software systems for processing and interpreting information on geophysical research of wells”. Bulletin of PNIPU Geology. Oil and gas and mining. 19(2), 162-174, 2019. T.19.№2. C.162-174. https://doi.org/10.15593/2224-9923/2019.2.6.
8. O.M. Ogorodnikova, Vichislitelnie metodi v kompyuternom injiniringe [Computational methods in computer engineering], 2013.
9. Yu.S. Zavyalov, B.I. Kvasov, V.L. Miroshnichenko, Metodi splayn-funktsiy [Methods of spline functions]. 1980.
10. A. A. Samarskiy, A. V. Gulin. Chislennie metodi, [Numerical methods], 1989.
11. S.P. Shariy. Kurs vichislitelnix metodov [Computing Methods Course]. 2020.
12. A.I. Grebennikov, Method splaynov in numerical analysis, 1979.
13. U. Khamdamov, H. Zaynidinov, “Parallel Algorithms for Bitmap Image Processing Based on Daubechies Wavelets”, In 2018 10th International Conference on Communication Software and Networks, ICCSN 2018 (pp. 537–541). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ICCSN.2018.8488270.
14. D. Singh, M. Singh, Z. Hakimjon, “Parabolic Splines based One-Dimensional Polynomial”, In 2018 SpringerBriefs in Applied Sciences and Technology (pp. 1–11). Springer Verlag. https://doi.org/10.1007/978-981-13-2239-61.
15. M. Singh, H. Zaynidinov, M. Zaynutdinova, D. Singh, “Bi-cubic spline based temperature measurement in the thermal field for navigation and time system”, in 2019 Journal of Applied Science and Engineering, 22(3), 579–586. https://doi.org/10.6180/jase.201909_22(3).0019.
16. H. N. Zayniddinov, O. U. Mallayev, “Paralleling of calculations and vectorization of processes in digital treatment of seismic signals by cubic spline”, in 2019 In IOP Conference Series: Materials Science and Engineering (Vol. 537). Institute of Physics Publishing. https://doi.org/10.1088/1757-899X/537/3/032002.
17. H. Zaynidinov, M. Zaynutdinova, E. Nazirova, “Digital processing of two-dimensional signals in the basis of Haar wavelets”, in 2018 In ACM International Conference Proceeding Series (pp. 130–133). Association for Computing Machinery. https://doi.org/10.1145/3274005.3274023.
18. Cherkashina Yu. A. Application kubicheskoy splayn interpolyatsii v zadachax prognozirovaniya funktsionalnogo sostoyaniya zdorovya detey. Natsionalnyy issledovatelskiy Tomskiy politexnicheskiy universitet. International Journal of Applied and Fundamental Studies. - 2016. - № 4 (chast 5) - C. 887-890.
19. Sukho Park, Byungkyu Kim, Jong-Oh Park, Youngin Kim, Geunho Lee. “Pressure Monitoring System in Gastro-Intestinal Tract”, Conference Paper May 2005. https://doi.org/10.1109/ROBOT.2005.1570298.
20. B.H. Jansen, “Analysis of biomedical signals by means of linear modeling”, Critical Reviews in Biomedical Engineering, 01 Jan 1985, 12(4): 343-392. http://europepmc.org/article/med/3893885.