Modelling Soft Tissue Deformation Based on Spatial Kriging

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Abstract. People can only obtain incomplete information when needle get into soft tissue. The actual conditions limit monitoring results. The kriging, as a statistical interpolation method, can effectively transform discrete point information into facial continuous information. On the basis of displacement data of pork soft tissue, the correlation parameter setting and optimal semi-variance model selection of kriging were studied to determine the kriging interpolation results. The results show that the accuracy of the kriging model can reach millimetre level, the maximum error is about 0.8mm, the average standard error is 0.35mm, and the calculation is simple. It can help doctors provide references when the soft tissue cannot be directly observed, and predict the deformation within the soft tissue.

1. Introduction
Percutaneous puncture technique is a common treatment method in modern medicine. Needle get into the soft tissue, reaching the target to achieve diagnosis, treatment, sampling, stimulation and other purposes. Most of target are concentrated in the internal organs of the body, the clinical application of tissue biopsy, local anaesthesia and blood RT, etc [1-2]. In these applications, the main causes of error are Imaging equipment resolution limit, image coordinate deviation, target measurement error, artificial error, as well as the position error caused by tissue deformation and needle deflection [3-5]. It is necessary to learn the biological characteristics of soft tissue to improve the precision and reduce the system error. The deformation prediction model of soft tissue, which connects needles and soft tissue, is of great significance for improving accuracy and reducing error [6]. At present, the common soft tissue models are mass-spring model, finite element model, meshless model, boundary element model and so on [7]. The mass-spring model and finite element model are the most widely used [8-9].

The mass-spring model is a method to construct the soft tissue model based on several sets of particle network structures with springs, and its deformation is mainly depending on the elastic coefficient of the spring [10]. Modelling is simple and classic, so it can support large-scale and high-real-time deformation calculations, many scholars has been improved it [11-17]. However, the accuracy of the calculation is low precision, which is limited by the precondition. Llinger et al [18] using genetic algorithm and others to optimize the mesh parameters of the mass-spring model to reduce the deformation error, but the computation is complex. Qiao et al [19] the mass-spring model of grid topology based on regular hexagon has been improved in stability and real-time, but the number of springs and particles is more. Choi et al [20] use parametric anisotropic spring-particle model to simulate the mechanical reaction of tissue. The simulation is very good, When the external force is stable. However, Once the external force is unstable, the deformation simulation will be different from the actual situation. Natsupakpong et al [21] study the elastic parameters of the spring-particle model, using tetrahedron and hexahedron to construct two-dimensional and three-dimensional...
grids. The ideal experimental results are obtained, but the calculation was more complicated. Basafa et al. [22] proposed to simulate the deformation of nonlinear and viscoelastic soft tissue by combining damper and spring-particle model, but the algorithm cannot solve the simulation of large deformation, it needs further optimization. Liu et al. [23] put forward that the spring-particle model and nonlinear anisotropic elasticity theory are combined to reflect the nonlinearity, anisotropy, viscoelasticity and quasi-compressibility of soft tissue, and the ideal results are obtained by experiment, but the calculation is more.

The finite element model is a kind of model which is popular with the development of computer technology, and this common simulation method is to solve the simulation results by analysing the numerical solution of partial differential equations, and the finite element method provides a very high precision soft tissue model [10]. However, the accuracy of the finite element model is directly related to the number of mesh generation, high-precision need to divide a large number of grids, resulting in too large a computation, so that real-time is very poor. Tang Xiangen [24] uses finite element model to simulate soft tissue deformation based on OpenHaptic environment, which ensures the authenticity and real-time requirements of deformation simulation, and provides important reference value for virtual surgery. Yin Lulu [25] builds the soft tissue of human face with finite element model, forming a multilayer finite element model containing skin, muscle and fat, provides a strong basis for further deformation after facial surgery, but there is no study on the bonding between skin and subcutaneous two layers. Moita et al. [26] improve the damping optimization of viscoelastic tissue by finite element simulation, and the experimental results show that the algorithm can improve the structure of model. Woraratsoontorn et al. [27] use finite element model to simulate the deformation of the real skull and soft tissue of the human body, and still needs to further improve the boundary conditions to improve the deformation effect and consider the influence of the surrounding tissues in the future. Sangpradit et al. [28] use the finite element model to simulate the movement and indentation of soft tissue under external forces. It can not only obtain high accuracy, but also accurately determine the depth and location of the tumor, and the model algorithm can conform to soft tissue and irregular organization in the future. Xie et al. [29] use the finite element model to simulate the three-dimensional friction contact analysis of Cosserat material, and the experiment proves the feasibility of the algorithm, but the calculation amount is very large.

In this paper, we propose a soft tissue prediction method based on Kriging to balance the contradiction between precision and real-time. Kriging is an excellent interpolation method. Only a small amount of information is required, the whole working face can be estimated by the semi-variogram function, and is the optimal linear unbiased estimation. It is possible to simplify the calculation and maintain high precision in the modelling by Kriging interpolation method. Therefore, this paper proposes to build a soft tissue model by Kriging, which greatly simplifies the calculation and improves the accuracy of the model. It reduces the puncture error to provide a reference for percutaneous puncture technique.

2. Kriging

2.1. Kriging model

Kriging model is one of the best interpolation models at present, and has been widely used in spatial interpolation in GIS in recent years. As one of the most widely used methods in kriging, the ordinary kriging interpolation mainly uses the raw data and the variation function of regional variables to estimate the linear unbiased optimal estimation of the regionalization variable of the unused sample point. On the premise that the expected data is normal distribution, it is considered that the expectation of the regionalization variable is unknown, and the approximate value of the interpolation point can be determined by the weight of the surrounding sampling point, and the regionalization variables with both randomness and structural, or spatial correlation in the spatial distribution are studied. The interpolation estimation formula is:
\[
\hat{z}_0 = \sum_{i=0}^{n} \lambda_i z_i
\]

As long as you give an expression of \[\lambda = [\lambda_1, \lambda_2, \lambda_3, \ldots] \]
any region variable in the interpolation space can be known. In order to minimize the difference between the estimate of \(\hat{z}_0\) and the true value of \(z_0\), the weighted coefficient \(\lambda\) must meet two conditions, namely: the optimal coefficient \(\min_{\lambda} \text{Var}(\hat{z}_0 - z_0)\) and the unbiased estimate \(E(\hat{z}_0 - z_0) = 0\).

2.2. Semi-variance function

Semi-variance function, as show in Figure 1, is the most important step in constructing kriging model, and its function selection directly affects the interpolation accuracy of the model. The selection of the theoretical model of semi-variance function is mainly based on the relationship between distance and semi-variance function calculation value, as well as the professional theory or experience to determine the appropriate theoretical model, but also can use scatter plot to speculate the appropriate theoretical model [30]. The common theoretical models are: exponential model, Gaussian model, spherical model and so on. The regional variables that are two points apart in space are recorded as \(z(x_i + h)\) and \(z(x_i)\) respectively, and the semi-variance function of \(N(h)\) pairs of zone variables with the same spacing of \(h\) in space is:

\[
r(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i + h) - z(x_i)]^2
\]

In the formula, \(r(h)\) is the value of the semi-variant function corresponding to all points of space distance \(h\), \(N(h)\) is the point logarithm of space distance \(h\), \(z(x_i + h)\) is the measured value of space \(x_i + h\), and \(z(x_i)\) is the measured value at space \(x_i\).

![Figure 1. Semi-variance function diagram](image)

The parameters such as nugget, partial sill, sill and range of the semi-variance function indicate the degree of spatial variation and correlation of regionalization variables. According to the theory of semi-variance function, the values of the two points in the same position should be equal, and with the increase of the distance \(h\), the numerical difference between the two points increases, until the initial base value is tended, and the interval distance between the sampling points is range. Because the sampling error and the existence of spatial variation make the two points very close, so that there is a nugget with a semi-variance function value of not zero. The Nugget/ Sill is called the substrate effect and is used to represent the variation characteristics between samples, reflecting spatial correlation, and if the value is greater, it means that there is more variation between samples caused by random factors. Then, we will use experimental data to build an accurate model.
3. Material

3.1. Test process
The choice of biological soft tissue material is about 25cm long, about 10cm wide, about 5cm thick of a shape of the regular pork leg (as show in figure 2). The meat in pork leg is evenly thick and easy to process into a shape-regular piece of meat to facilitate the insertion of identifiers. Pork leg meat has typical soft tissue mechanical characteristics of anisotropy, and its mechanical properties in the fiber direction of identical and vertical are different. Its mechanical properties can be obtained by SHPB experiment [31], in the case of strain rate of 0.02/s, the modulus of fiber direction of identical the is 121.00± 28.76kPA, the ultimate strength is 63.73± 18.53kpa, the failure strain is 0.934± 0.189; the modulus of fiber direction of vertical is 47.60± 19.30kpa, the ultimate strength is 22.94± 3.63kpa, failure strain is 1.077± 0.111[32]. The markers (as show in figure 3) use an iron nail with a diameter of about 2.3mm and is arranged at a 1.5cm distance interval.

The meat of the inserted markers is placed on the special fixture, and the puncture experiment is carried out by using the three-coordinate puncture system, and the B-ultrasound image is collected by the ultrasonic probe placed on the meat. Because of the limitation of the scanning width of the ultrasonic probe, the internal situation of the whole organization cannot be observed with one scan. The B-ultrasound images collected sequentially must be stitched together. Stitched image is generally jpg format, not convenient for direct image processing. PS is generally used to convert its format to BMP format and then image processing. Using MATLAB to binarization, improve the contrast of the image to reduce the difficulty of subsequent processing, corrosion removal of small, discrete, large area of noise in the image, expansion is amplifying and recover the identifier image which remove the noise after, noise reduction to remove the large noise spots which corrosion still exists after. The marker marks the centroid of the remaining image and sends its coordinates to the specified location, and finally converts the coordinate units on the image from pixels to millimetres. The position of the identifier in the soft tissue can eventually be obtained. The displacement of the identifier in the puncture process can be obtained by comparing the coordinate position of the image with different puncture depth. Figure 4 is a B-ultrasound image when the needle puncture is completed, and the

![Figure 2. The soft tissue used](image1)

![Figure 3. Marker](image2)
identifier is not completely identified in the image due to equipment limitations and other reasons (as shown in Figure 5). The displacement of 37 markers can be obtained by comparing it with the B-ultrasound image when the puncture is not beginning.

![Figure 4. needle puncture soft tissue B-ultrasound image](image)

**Figure 4.** needle puncture soft tissue B-ultrasound image

![Figure 5. Marker coordinates](image)

**Figure 5.** Marker coordinates

3.2. Data processing
Data normal distribution is the premise of applying spatial interpolation of kriging method, using histogram to verify the normal distribution of the data. In this paper, logarithmic transformations are adopted for each identifier displacement data, and the skewness and kurtosis of the data before and after the transformation are compared (as shown in table 1). The closer the skewness and kurtosis are to 0, the more the distribution of data tends to be normal. Therefore, in this paper, the displacement data is used as the basic data of the spatial interpolation semi-variation function of kriging method by logarithmic transformation.

| Sample points (PCs) | Average (mm) | Minimum value (mm) | Maximum value (mm) | skewness Before conversion | skewness After conversion | kurtosis Before conversion | kurtosis After conversion |
|---------------------|--------------|--------------------|--------------------|----------------------------|--------------------------|--------------------------|--------------------------|
| Displacement        | 38           | 0.7353             | 0.09881            | 3.00501                    | 2.783                    | -0.455                   | 13.473                   | 4.769                    |

3.3. Kriging values
By substituting the experimental data into different semi-variation function models, the performance of different semi-variation function models under 5 indexes has its advantages and disadvantages, and the accuracy evaluation results are shown in table 2.
Table 2. interpolation accuracy analysis of different semi-variation functions

| Semi-Variance Model | Mean   | Root-Mean-Square | Mean Standardized | Root-Mean-Square Standardized | Average Standard Error |
|---------------------|--------|------------------|-------------------|-------------------------------|-----------------------|
| Stable              | -0.0289| 0.4497           | -0.0756           | 1.3086                        | 0.3482                |
| J-Bessel            | -0.0318| 0.4572           | -0.1486           | 1.5345                        | 0.3403                |
| K-Bessel            | -0.0296| 0.4496           | -0.0771           | 1.3109                        | 0.3470                |
| Hole Effect         | -0.0120| 0.4549           | -0.1075           | 1.4546                        | 0.3645                |
| Rational Quadratic  | -0.0354| 0.4492           | -0.0892           | 1.2990                        | 0.3387                |
| Gaussian            | -0.0144| 0.4601           | -0.0938           | 1.4115                        | 0.3603                |
| Exponential         | -0.0256| 0.4512           | -0.0624           | 1.2732                        | 0.3578                |
| Pentaspherial       | -0.0270| 0.4478           | -0.1018           | 1.4102                        | 0.3387                |
| Tetraspherial       | -0.0206| 0.4482           | -0.0837           | 1.3732                        | 0.3460                |
| Sperical            | -0.0116| 0.4466           | -0.0691           | 1.3439                        | 0.3529                |
| Circular            | -0.0198| 0.4501           | -0.0571           | 1.3120                        | 0.3591                |

Accuracy standards includes 5 evaluation indexes of Mean, Root-Mean-Square, Mean Standardized, Root-Mean-Square Standardized, Average Standard Error, in which the closer the Mean and Root-Mean-Square is 0, the better, the smaller the Average Standard Error and the Mean Standardized, the better the Root-Mean-Square Standardized is closer to 1. Because the spatial interpolation scale range of this paper is very small, the average standard error and the root-mean-square of each point are the main precision evaluation indexes, combined with the mean, the mean standardized, the root-mean-square standardized and so on. The semi-variation function model of the identification point displacement is the highest precision of the spherical model.

![Figure 6](image)

Figure 6. Spherical model semi-variance function model

Figure 6 is a spherical model semi-variance function diagram, in which the scatter represents the semi-variance of the data, the x-axis is the distance between the data, the curve is based on the scatter plot of the spherical model, the dotted line represents the variance of the data. The specific expressions of the spherical model are:

$$
\gamma(h) = 0.0001 + 0.3121 \left( \frac{3}{2} \frac{h}{23.7} - \frac{1}{2} \frac{h^3}{23.7^3} \right)
$$

The specific parameter nugget 0.0001, the partial still 0.3121, the still 0.3122, the range 23.7. When the ratio of nugget to sill is ≤25%, the spatial autocorrelation degree of variable space is strong, and if the ratio is between 25% and 75%, it is medium space autocorrelation level, and if the ratio is
≥75%, it is weak space autocorrelation level. The nugget/still is 0.0003. Therefore, the experimental data has a strong spatial correlation, and it is very suitable to use the Kriging model.

4. Results and analysis

In order to better reflect the change of the displacement of the marker, ArcGIS uses the non-isometric grading method to classify the displacement of the identifier, which is divided into 10 levels, of which the first 7 levels are small and detailed, reflecting the displacement change, and the latter level 3 is relatively large to reflect the deformation of the needle tip site. From Figure 7, it can be seen that the displacement takes the needle tip part as the core and gradually weakens to both sides. The concrete performance is that the displacement of the needle tip part changes the most, followed by the needle shaft. The active needle axis is centred and the displacement decreases to both sides, and presents a strong anisotropic characteristic, in the direction of the CIS displacement is significantly greater than the vertical fiber direction, and the results of block gold effect analysis is consistent.

![Figure 7. Soft tissue kriging model and schematic diagram](image)

From the error distribution (as shown in Figure 8), it can be seen that the model precision constructed by Kriging interpolation method fully meets the requirements. The maximum error is about 0.8mm, which fully meets the requirements of millimetre grade accuracy for needle puncture surgery. Most of the errors are relatively small, about 0.5mm and distributed on both sides of the needle body. This part of the sampling point is denser, so the interpolation accuracy is higher. In the needle part, in order to prevent the needle tip from colliding with the marker, the identifier is set less. There are few sampling points around these sampling points and there is a lack of spatial information for interpolation, so the error is larger than elsewhere. Especially the needle tip site spatial information is the most lacking, the error is the greatest.

![Figure 8. error distribution](image)

5. Conclusions and future work

The displacement of soft tissue when the needle get into it has a strong correlation in space. The suitable semi-variation function can improve the precision of kriging model. In this paper, displacement data of soft tissue are obtained by image processing. The data are transformed by logarithmic transformation to make the data obeys normal distribution. Comparing the accuracy of each semi-variation function model to select the most suitable one. It is most appropriate semi-variation function is spherical model by comparing. Finally, the Kriging interpolation results and error distribution are obtained. The results are consistent with the actual situation, and the error also meets the requirements.
Compared with the traditional soft tissue model, such as the mass-spring model and the finite element model, the advantage of the Kriging is that it can simplify the calculation with high precision, so its practicality is greatly improved. In the clinic process or training system, the deformation is required to be feedback to the physical. In future work, kriging model will add time factors to the to improve prediction and provide the real time information.

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