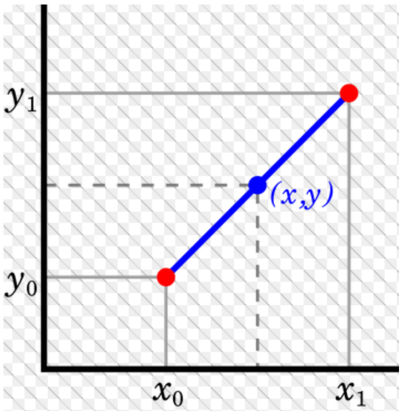

Figure 2. Linear interpolation

3.2 Cressman Interpolation

The cressman interpolation finds the data for the grid that consists of latitude and longitude grid. So many passes are to be done through grid continuously to increase the precision value of influential radii value. Every pass calculates the new value for the grid using its correction factor. The influential radius value is mentioned as the higher radius from the point of grid to the station. The station beyond the influential radius does not have bearing on the point of grid. The correction factor for cressman interpolation is calculated by analyzing every station which is within the limit of influential radius. An error of a station is described as the variation of the station values and the interpolated value from the grid to the particular station value. Distance weighted formula is applied to the errors that are found within the influential radius level to reach the corrected value of grid point. The correction factor is then used for all grid points before the next pass is done. So the grid point that is nearer will get the most weight. Figure 3 illustrates the cressman interpolation on location prediction based on the cressman weight function given below. If the distance is increased, the total observations are having less weight. The cressman function finds the weight by using the formula below:

$W = (RA^2 - ra^2) / (RA^2 + ra^2)$

Where,

RA - Radius of Influence

ra - Distance between the station & the point.

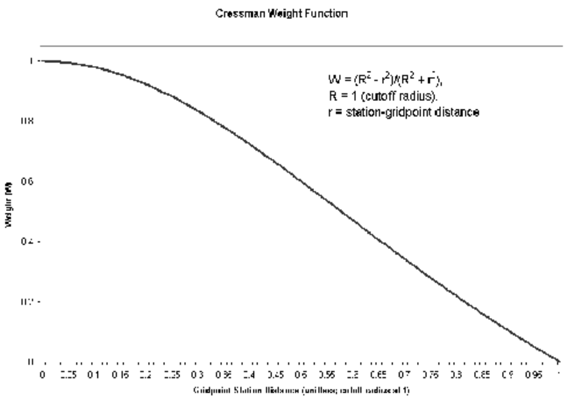

Figure 3. Cressman Analysis

3.3 Weaver Analysis

Weaver analysis is diverse from the Cressman analysis where a weaver function can be used to perform unweighted interpolation. The observations that are made in the grid box are utilized to calculate the value which is being interpolated. Here the weaver function is not used for calculating the weighed values of observations. Each grid box has the value by calculating an arithmetic average function of the observation. Figure 4 shows the example of Weaver Analysis function which is mainly created for Climate Prediction Center for predicting and analyzing the climate changes

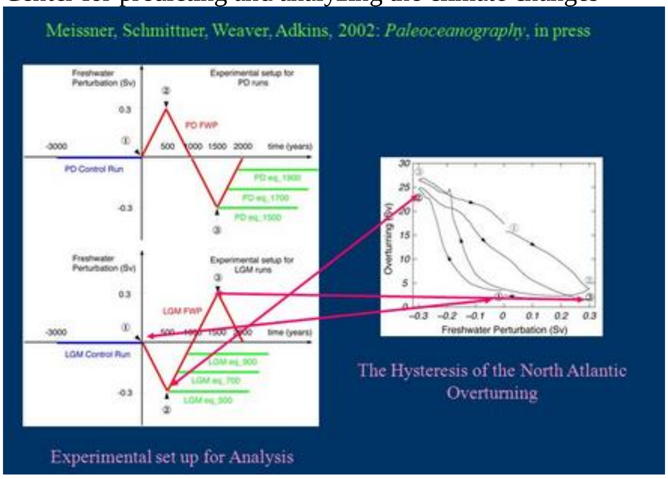

Figure 4. Analysis of Climate changes using weaver analysis

3.4 Inverse Distance Weighted (IDW)

The IDW interpolator always proceeds with the points that are farther away rather than closer one. The points will be either specific or the points in specific radius. This is used to determine the possible output of the location. High variable data makes use of IDW because of easy returning process to collection site and easy to register a new value that are different from original one within the certain area. IDW interpolator implements the assumptions that are closer and alike. IDW uses the values surrounding the prediction location to predict the unmeasured location. The predicted location will be more influential when it is closer. The Figure 5 show the projection and location prediction based on the given input from the open surface area.

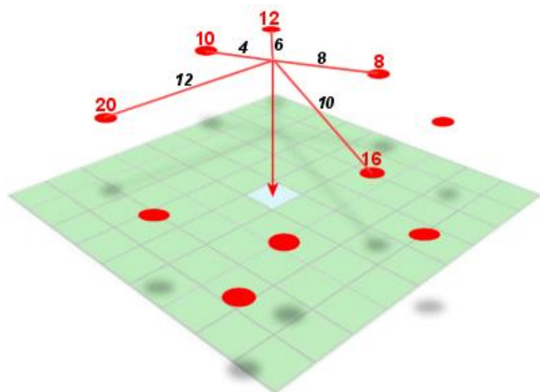

Figure 5. Inverse Distance Weighted method

3.5 Natural Neighbor Inverse Distance Weighted (NNIDW)

Interpolation and extrapolation are implemented by NNIDW method. It is facilitated with the cluster of scatter points and manages the input datasets that are large. It is a geometric estimation method which utilizes the neighboring regions around the points in the set of data. This interpolator makes up the exact surface model from the data ser and also it's very distributed or very linear. Figure 6 shows a sample natural neighbor IDW interpolation method

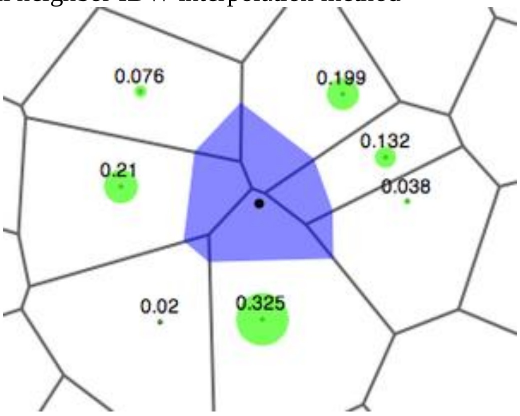

Figure 6: Natural Neighbour Inverse Distance Weighted Interpolation

3.6 Spline Interpolation

Spline Interpolation utilizes a mathematical functionality which minimizes the curvature into a smooth surface. It passes through the input points provided. The spline interpolation is made for fixing the mathematical function to the specific nearer input points when the sample points are considered. The spline interpolation is categorized into regularized spline and tension spline. The first method makes a smooth and even changing surface that consists of values lying outer to the given sample range. Three kinds of derivatives considered as slope, rate of change in slope and change in rate of second derivative for calculations. The second method exploits first and second derivatives and it considers many points for calculations aiming to smoother surfaces. So the computational time will be high for this interpolation. Figure 7 represents a natural spline that utilizes a mathematical function to predict the point over smooth surface areas

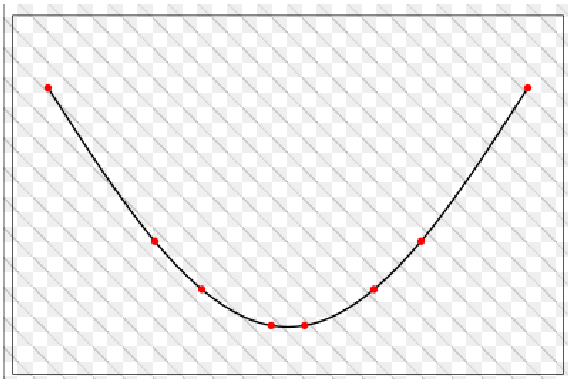

Figure 7: Spline Interpolation

3.7 Kriging Interpolation

Kriging is a geostatistical interpolation that believes both distance and the variation degrees to estimate the unknown data points [7]. A surface is made based on the points identified using Z-values. The direction of points and the distance depends on the points that are spatially correlated as mentioned in the kriging. Kriging interpolation is an appropriate one when the data is spatially correlated. This interpolation is used in improvisation of soil science and geology. Figure 8 shows the kriging interpolation where the points are predicted based on the distance that are spatially correlated.

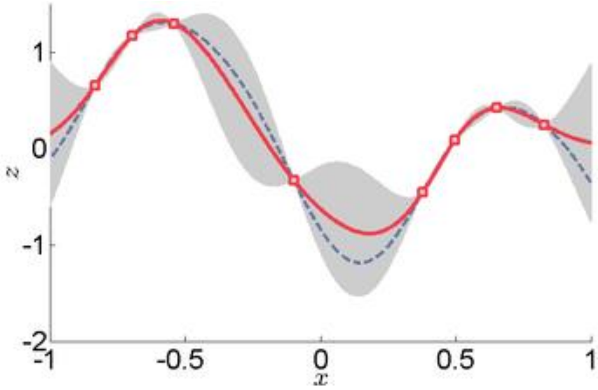

Figure 8: Kriging Interpolation

The construction of the kriging interpolation is given based on sum of data as follows:

$$Z(p0) = \sum_{x=1}^{N} Wx \, Z(px)$$

where:

$Z(p_x)$= the measured value at the x^{th} location

W_x = an unknown weight for the measured value at the i^{th} location

$\mathbf{p_0}$ = the prediction location

N = the number of measured values

Kriging Interpolation is of few types given below

a. Ordinary Kriging

Ordinary kriging implements the function F(**s**) = c + ε(**s**), where c is an unknown constant. This assumption is rejected for sometimes because ordinary kriging is either using semivariograms or covariances. It also uses transformations which lead to measurement error

b. Simple Kriging

Simple kriging gives the function as F(**s**) = c + ε(**s**), where c is a known constant. Here the Simple kriging can make use of semivariograms or covariances. It also considers transformations that leads to measurement error.

c. Universal Kriging

Universal kriging makes use of the function F(**s**) = c(**s**) + ε(**s**), where c(**s**) is a deterministic function. It can make use of either semivariograms or covariances and use transformations. It also leads to measurement error.

d. Indicator Kriging

Indicator kriging provides the function B(**s**) = c + ε(**s**), where c is an unknown constant and B(**s**) is a binary variable. The binary data is created through some threshold value obtained from continuous data or the observed data from 0 to 1. It is same as ordinary kriging method that either use semi variograms or covariances except the use of binary values.

e. Probability Kriging

Probability kriging makes the model with B(**s**) = B(F(**s**) > c_t) = c_1 + ε_1(**s**), Z(**s**) = c_2 + ε_2(**s**), where B(**s**) is a binary variable created by threshold indicator, B(F(**s**) > c_t) and c_1 and c_2 are unknown constants. The random error is found on ε_1(**s**) and ε_2(**s**), for checking autocorrelation for themselves and cross-correlation between the two errors ε_1(**s**) and ε_2(**s**). It's identical to indicator kriging, but exploits cokriging for the betterment of processing. Probability kriging exercises semivariograms or covariances with cross-covariances, and transformations and does not authorize for measurement error.

f. Disjunctive Kriging

Disjunctive kriging assumption directs to f(F(**s**)) = c_1 + ε(**s**), where c_1 is an unknown constant and f(F(**s**)) is an arbitrary function of F(**s**). The function f(F(**s**)) = B(F(**s**) > c_t),for indicator kriging is a container of disjunctive kriging. To attain disjunctive kriging, a bivariate normality assumption and approximations is needed for the function fi(F(si)) where the assumptions and solutions are difficult to validate. Disjunctive kriging use either semi variograms or covariances with transformations which is not allowing the measurement error.

4. Pros and Cons of Interpolation

The Table I illustrates the advantages and disadvantages of using various interpolation techniques over location prediction.

Table 1: Pros and Cons of interpolation

Inter po-lation	**Advantages**	**Disadvantages**
Linear	-The rate of change within a segment is constant	-Discontinuities in derivative exist at all key frame points.
Cressman	-easy and computationally speedy -Added accuracy than other methods	-Unstable if density is higher than station density -Sensitive to errors observed -Analysis gives the unrealistic extreme grid values, -Does not consider the distribution of observations related to each other. -Consistent results varies with observed one
Weaver Analysis	-Simple and speedy -More accurate -Considers only the realistic values	-For missing data the spatial resolution is increased -If resolution decreases, the observations have less impact on values interpolated -If resolution increases, grid boxes will be found as missing. -Avoids the influence of stations outside the grid box. -Potential errors improved at low spatial resolutions
Inverse Distance Weighted	-Can guess changes in terrains -Well interpolated even space points -Sample points used to influence cell values based on numbers.	-Cannot guess values and its limits -Not suitable for steep areas
Natural Neighbou-r Inverse Distance Weighted	-Handles large numbers of points	
Spline	-Helpful for approximation of minimum and maximum points. -Generates even surface	-Faulty lines are not given properly for smoothing -If sample points are closely related and is having differences in values, Spline interpolation will not work
Kriging	-Used for Soil Erosion, Siltation Flow, Lava Flow and Winds -Direction and nature go beyond limited level of point values	-it does not pass through any of the given points which affects interpolated values.

5. Conclusion

In this paper the fundamental concepts of wireless sensor networks have been discussed and the various common phenomenon identification methodologies are discussed. The introduction is about spatial correlation, the interpolation technique and the use of interpolation in identifying the new points on an open surface area. Various models have been implemented for localization of sensors such as probabilistic approach, MCL algorithm, Random walk based algorithm, Temporal Spatial model, PSO based model and Scan localization System etc. for predicting a point for sensor localization. The localization is mainly focusing on the network optimization in terms of cost and energy efficiency. To overcome the previous implementations the interpolation techniques are implemented. This is fully based on the prediction of new surface points if the points are already predicted and given as an input. The paper is discussed for various techniques for sensor localization and various interpolation methods for variety of prediction methods used by various applications in sensor networks through its advantages and disadvantages.

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