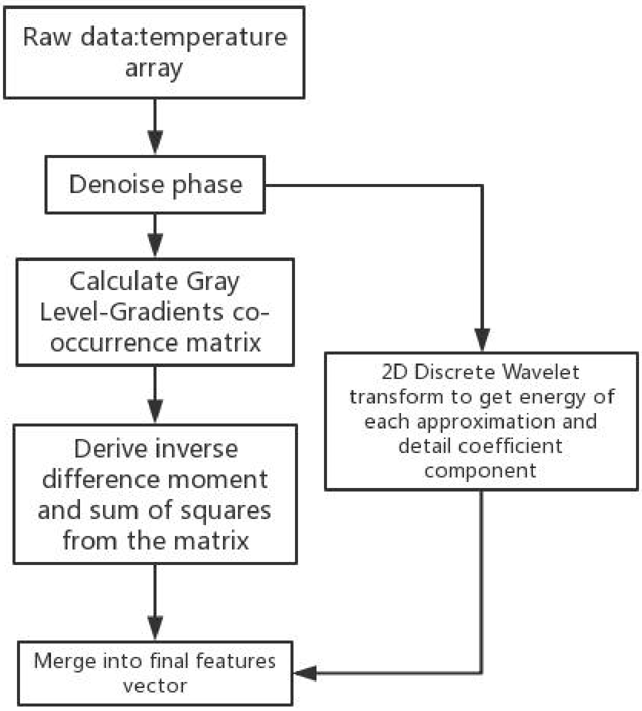
Overall:

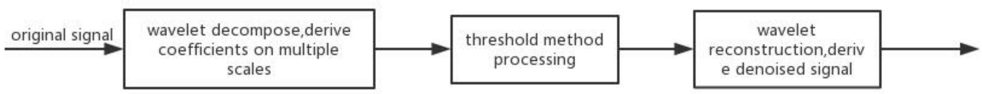
The raw data derives from the temperature array where each element corresponds to a pixel in the original image and represent the corresponding temperature.

Before process the raw data,we denoise the raw image to reduce white noises lying in the data through wavelet transform.

By calling *features_extraction.features(denoised data)*,we could get the finalized features vector which contain there major features.



Denoise:



Approximation and details are normally utilized in wavelet analysis: approximation corresponds to signals on high scales with low frequency while details correspond to signals on low scales with high frequency. For noise-corrupted signals, the energy of noise component mainly lies in the detail part.

For the denoise process through wavelet, choice of wavelet base function, decomposition levels, selection of threshold values and threshold functions all have possibly high influence on effects of the denoise process:

(1) For wavelet base function,Bior 3.5 has been shown to be suitable(Compactly supported

biorthogonal spline wavelets for which symmetry and exact reconstruction are possible with FIR filters).

(2) For decomposition level, the higher the level, discrepancies between noise and valuable signal are more noticeable so that they are more easily separated; while, the reconstructed signals are more likely to be distorted which worsen the effects of the denoise process.It's necessary to select a appropriate decomposition level to tackle this conflicts. The level could be set by variables *denoised_level* in the code.For test images of size 156*206,it's set to 3 in the code.

(3) For threshold value and function, hard threshold function have better performance on mean square error than soft threshold function, but would create additional oscillation and jump point in the signal so that smoothness of original signal can't be warranted. Soft threshold function can generate wavelet coefficients with better continuity wholly and no additional oscillation, but the goals towards compression of signals have high priority so that signals could be distorted at certain degrees. A eclectic way of merging hard and soft threshold function is applied in the code to improve performance.

Features from Co-occurrence Matrix:

Gray level-gradients co-occurrence matrix reflects the mutual relationship between gray level and gradients of pixel points in the image-two fundamental elements of an image. Gray level of pixel points form the basis of an image while gradients contribute to edges or boundaries of an image. Spatial relationship between a pixel and its surrounding pixels could also be provided in the gray level-gradients space.In this way, texture of images could be described.

Gradients are normally extracted by gradient operator or edge detection operator like sobel, canny or reborts. Based on normalized Gray Level-Gradient Co-occurrence Matrix, a series of second order statistical properties(texture features) could be calculated, which includes small gradients dominance, big gradients dominance, gray level asymmetry, gradients asymmetry, energy, gray level mean, gradients mean, gray level variance, gradients variance, correlation, gray level entropy, gradients entropy, mixed entropy, inertia, inverse difference moment and sum of squares and so on. Obviously, to enhance the performance of the learning process, the selection of these features is necessary to obtain only these ones which are the most discriminative and weakly correlated. Research has shown that inverse difference moment and sum of squares are suitable options. (*M. Kociolek, A. Materka, M. Strzelecki, P. Szczypinski, "Discrete Wavelet Transform-Derived Features for Digital Image Texture Analysis", Proc. International Conference on Signals & Electronic Systems ICSES'2001, Lodz, 18-21 September 2001, pp. 111-116*)

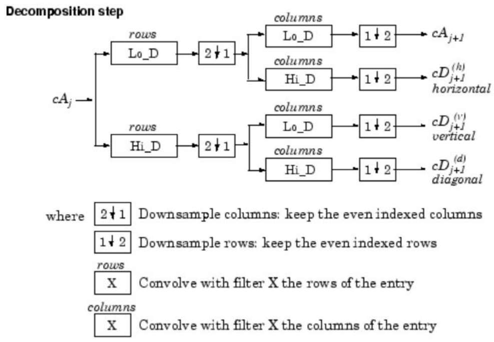
Features from 2D DWT:

For images, an algorithm similar to the one-dimensional case is possible for two-dimensional wavelets and scaling functions obtained from one-dimensional ones by tensor product.

This kind of two-dimensional DWT leads to a decomposition of approximation coefficients at level j in four components: the approximation at level j+1, and the details in three orientations (horizontal, vertical, and diagonal).

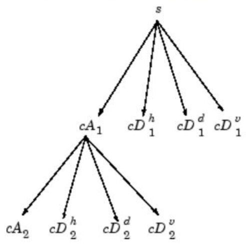
The following chart describes the basic decomposition step for images:

Two-Dimensional DWT



Initialization $cA_0 = s$ for the decomposition initialization

So, for J=2, the two-dimensional wavelet tree has the form



Gabor filter has been proven to have quite an advantage over texture extraction,and is realized and applied in the code.

The rational for the choice of levels is the maximum level where at least one coefficient in the output is uncorrupted by edge effects caused by signal extension. Put another way, decomposition stops when the signal becomes shorter than the FIR filter length for a given wavelet. Training images we use in this case contain the size so that they share the same maximum decomposition level.

After decomposing the denoised array, we could derive approximation and detail coefficients at each scales. For each coefficient array, we calculate the energy(sum of squares) and they are all added to the final features vector. Since all training images have the same decomposition level, so they share the same amount of approximation and details component after wavelet transform.As a result, features vector have the same size.