2.2.2 Smoothing the directional field

After the directional field is resampled, it goes through a second smoothing stage. This time, it consists of a convolution with a $3 \times 3$ averaging box filter. This filter can be applied to each vector component separately; hence, they can be implemented very efficiently. If the direction found comes from a good quality region, then the neighboring regions will very likely have the same direction and will not affect it. But if the region is noisy, then the direction will be corrected by the general trend. It is important to note that the amount of smoothing applied has to be constrained; if not, regions with large changes in the ridge directions (e.g. cores and deltas) will be lost in the process. Figure 9 shows the improvement obtained in the SP detection for fingerprint NIST-14 s0024310.

![Figure 9: Smoothing of the directional field for NIST-14 s0024310.](image)

(a) delta detection without smoothing; (b) un-smoothed directional field; (c) improvement in the delta detection due to the smoothed field shown in (d).
2.2.3 The SLNN

The SLNN used is similar to the one proposed by Trenkle, but in our work, we used the weighted directional field resulting from the averaging procedure. The point for including the weight, $\lambda$, is that it was expected the neural network to give low responses, not only in the cases of non-singular point patterns, but also in the cases of noisy singular point patterns, where the confidence of the directions is low.

The SLNN represents a square window that moves over the directional field in steps of size $sz$, taking sample blocks. The size of the sample blocks $(bz)$ needs to be large enough to include the singular point and neighboring regions ($bz = 8 \times 8$ was selected). The network produces for each jump a response in the range $[0,1]$. This could be interpreted as a measure of the probability that the input pattern is the SP searched. Then, the overall output of the SLNN, after going through all the blocks, will be a confidence map of the existence of the desired pattern. The resolution of the output map is dependent on the step size $sz$. To avoid aliasing, we choose an overlapping step size $(sz = 1)$ in our system.

For training the network, overlapping samples of sections of 40 randomly chosen NIST-14 fingerprints were extracted, mimicking the way the SLNN operates. Those patterns for which the manually located core (delta) fell inside the SLNN box were marked as SP regions, or otherwise, as non-SP regions. Two training sets resulted, one containing core and non-core patterns and the other containing delta and non-delta patterns. With the aim of balancing the training sets (i.e. have similar number of SP and non-SP regions), they were artificially extended to 700 samples each by considering possible rotations of the patterns.

The network architecture chosen was a Multilayer Perceptron (MLP), with three layers (included the input layer). The input layer consists of 128 nodes corresponding to $bz \times bz \times 2$ components per vector. The output layer consisted of one log-sigmoid node motivated by the fact that we wanted the network response to correspond to the probability of the input pattern being a SP.

Experiments conducted to determine a convenient number of hidden units showed that 16 nodes produced the least number of false-positive and false-negative results. Fewer or more hidden nodes increased the number of false alarms or missed SP.

The same structure was used for the two networks, one for detecting cores and another one for detecting deltas. Backpropagation was chosen as the learning rule. Figure 6(b) shows the scaled response of the SLNN for fingerprint NIST f0000043 (shown in Fig. 6(a)).

2.2.4 SP area location and following steps.

Once the SLNN has built the confidence map for the SP being searched, a square area of maximum response is located. The confidence measure given to the iteration is the normalized sum of SLNN output values corresponding to the region of maximum response. This region is the work area for the next iteration; i.e. resampling will only take place in this bounded region. If the confidence measure is above a certain threshold, the system proceeds from the stage described in 2.2.1. Figures 6(c) and 6(d) show the area of maximum response found for two different resolutions. Figures 6(e) and 6(f) depict the resulting detection of SP after the iterative procedure.

2.3 Ridge-count process

Once the core and delta points are located, the fingerprint skeleton is built to get the ridge count. The skeletonizer was adopted from a report by Bergengruen, and is briefly described here.