Chapter 4 – Results

4.1 Pattern recognition algorithm performance

The results of analyzing PERES data using the pattern recognition algorithm described in Chapter 3 are presented here in Chapter 4 to assess the algorithm’s performance. A discussion of PERES system performance is also provided to clarify the relationships between the performance of the pattern recognition algorithm, noise and clutter in the data. Recommendations for improving the performance of PERES are provided, particularly when they have potential to increase the accuracy of the pattern recognition algorithm.

4.2 PERES system performance in use

As a prototype, the PERES is designed to collect GPR data that can be analyzed to detect locations of distress and reinforcing steel in bridge decks. A variety of deck configurations exist which are desirable for the system to perform well on, even though they present challenges to GPR performance. The current PERES can perform well for many of these situations (as detailed in section 4.3), but limitations do exist. Bridge deck features that adversely affect the performance of PERES include asphalt overlays and large concrete cover depths. Bridge decks with asphalt overlays and/or large concrete cover depths create significant impediments to detecting features of interest using PERES. Asphalt overlays increase the distance a radar pulse must travel through lossy materials, (both asphalt and concrete), on the round trip between the PERES antenna and features of interest inside the deck. This increases the attenuation of the radar pulse, which reduces the signal to noise ratio of the collected data. In addition, the interface between asphalt and concrete, (two materials that generally have different dielectric properties), can produce ringing in the return waveform. This phenomenon occurs when reflected energy from an incident radar pulse strikes a material interface or
Figure 4.1 Experimental slab 1 with asphalt placed on its surface.

Figure 4.2 PERES waveform sampled from data taken over the slab in Figure 4.1.
the radar antenna itself as it returns from a target. A portion of this energy can be reflected back toward the target object and subsequently reflect off of target features in the deck to produce a secondary response, or clutter. This ringing can mask reflected returns from features of interest in the deck when the time delay between the initial return and the ringing pulse produces a response in the time window of the feature of interest.

An example of the ringing that asphalt overlays can give rise to is exhibited in a raw waveform, (Figure 4.2) collected using PERES over the deck configuration shown in Figure 4.1. Based on an analysis of data from this deck configuration, (and confirmation of peak assignments based on tests of the same concrete deck with an 8 cm thick asphalt piece), peaks 1 and 2 correspond to the front surface of the asphalt overlay and the asphalt to concrete interface, respectively. The time difference between peaks 1 and 2 is equivalent to the time difference between peaks 2 and 3, which indicates it could be due to ringing. The time difference between peaks 3 and 4 is also equivalent to the time difference between peaks 1 and 2. These equivalent time differentials indicate they do result from ringing and this interpretation is confirmed when signals from a deck with 8 cm of asphalt cover reveal analogous features. The unusual signal amplitude variations can be attributed to exponential gains applied to the near and far time windows of the signal.

Responses in PERES data obtained from asphalt covered decks in the FHWA inventory exhibit similar ringing patterns to those exhibited in Figure 4.2. This phenomenon combined with attenuation has prevented PERES from imaging reinforcing steel or other features of interest in asphalt covered bridge decks. A plot of raw data from bridge deck R4, (deck section diagram in Figure C10, Appendix C), is presented in Figure 4.3 to illustrate typical PERES data from an asphalt covered bridge deck. This plot presents the data collected during a single pass of the PERES antenna along its rail. The plot displays the waveforms collected across the 2.05 meter real aperture, (along the rail), representing the magnitudes of the waveforms in gray scales defined on the color bars. The notable features in the data include abrupt changes in the waveforms at width=15 cm and width=190 cm and the reflection from the top surface. The abrupt changes in the waveforms at the noted widths occur due to the antenna traveling over the
Figure 4.3 Section view of raw PERES data from bridge deck R4.

Figure 4.4 Raw PERES response to an aluminum pole.
Figure 4.5 Experimental slab 2 with reinforcing steel at varying cover depths.

Figure 4.6 Cross section image of reconstructed PERES data from experimental deck 2 (reflected magnitudes, black=0, white=$19\times10^4$).
edge of the bridge deck specimen. Therefore, the responses at the two extremes of the synthetic aperture width are attributable to responses traveling through air to the laboratory floor. This allows the response to specimen edges to be observed in the collected data.

If reinforcing steel, oriented transverse to the direction of antenna motion, were producing a significant response in this data, parabolic responses would be observed in the raw data, with maxima at a range corresponding to the proximity of the antenna to the reinforcing steel. The parabola would be generated by the changing range from the antenna to the individual piece of reinforcing steel, as the antenna moves across the synthetic aperture. An example of a parabolic response generated by PERES as it collects data over a synthetic aperture is illustrated in Figure 4.4. An aluminum rod is located at a range that produces the strongest response, (directly in front of the pole), at 1.4 nanoseconds and a width of 10 cm. As the antenna moves across the synthetic aperture, the distance from the antenna to the pole increases, which increases the time required for a radar pulse to travel from the antenna to the pole and back. Viewing the waveforms across the synthetic aperture, this produces the parabolic response observed in Figure 4.4. These parabolic responses to reinforcing steel, across the synthetic aperture, are not observed in the raw PERES data from bridge deck R10, (Figure 4.3). In addition parabolic responses are not observed in the raw PERES data from any of the asphalt covered bridge decks in the FHWA inventory, (R2 through R6). This indicates that responses to the reinforcing steel in the PERES data for asphalt covered decks are masked by clutter and noise.

As concrete cover depth increases, the reflected responses from features of interest at deep cover depths become attenuated, and the signal to noise ratio is reduced, (Section 1.1.3). This reduction in the signal to noise ratio with cover depth can significantly affect the performance of PERES. The effect is clearly illustrated in PERES test data from the fabricated deck section pictured in Figure 4.5. The concrete mix design for this deck is provided in Appendix E, Table E3. This deck section contains reinforcing steel with varying cover depths from 3 cm to 18 cm in increments of 3 cm. The reconstructed PERES data from this deck section, (Figure 4.6), illustrates that reinforcing steel is effectively detected down to 9 cm. Reinforcing steel at deeper cover depths than
9 cm produce responses that are not distinguishable from noise and clutter for this deck. The depth at which features of interest can be detected will vary depending on the dielectric properties of the bridge deck materials, but the results from this experimental deck, (with a typical bridge deck concrete mix design), provide a valuable reference.

Many different bridge deck configurations are found in the real world which effect the performance of PERES. The current PERES design images features of interest best for bare concrete bridge decks, (no asphalt overlay), that have shallow cover depths, (less than or equal to 9 cm for the test described in this section). Design changes can be made to improve the performance of PERES, when a second generation prototype is built, (Section 4.5) but it is important to understand the practical advantages and limitations of the current system. Understanding the performance characteristics of PERES provides useful information for judging the results produced by pattern recognition algorithms.

4.3 Measurements of algorithm performance

The three functions the pattern recognition algorithm performs are, measuring mean concrete cover depth, determining the location and orientation of individual reinforcing steel pieces in decks and detecting locations of distress in decks. The performance of the algorithms that carry out these functions is evaluated based on comparisons to measurements and standards available at the FHWA NDE Validation Center. These measurements and standards are specified in the following sections, where they are compared with pattern recognition results.

4.3.1 Mean concrete cover depth

Concrete cover depth is a critical measurement for bridge decks because it affects the initiation of reinforcing steel corrosion and the rate at which the corrosion progresses, (Section 1.1.1). The cover depth also relates to the expected location of delamination distress (Section 1.1.1). The process described in Section 3.3.1 is used by the pattern recognition algorithm to determine the mean concrete cover depth, which is a representative measurement of the concrete cover depth in the area under analysis.
Figure 4.7 Mean cover depth comparison between algorithm and measured or design values.

Figure 4.8 Mean cover depth comparison between algorithm and expert values.
Results from the algorithm are presented for seven bridge deck sections from the FHWA NDE Validation Center inventory. Measurements used for comparison to the algorithm results include expert interpretation of PERES data, measured cover depth at cut deck section edges and design values used to fabricate two bridge deck sections.

The measurements that were made for comparison with the pattern recognition algorithm results were carried out in the following way. A ruler was used to determine concrete cover depths to the nearest 0.6 cm (0.25 in). These ruler measurements were designated “measured values” and provide a basis for comparison that is independent of the radar data. Expert interpretation of the reconstructed PERES data was carried out by inspecting individual plan view layers of the data. For all of the reconstructed PERES data, these tomographic layers were 0.1 cm deep. A layer was selected in the reconstructed response from each deck where the top surface of the reinforcing steel mat was clearly imaged. The depth of this layer was designated as the “expert value.”

Figure 4.7 presents a comparison between algorithm values and measured values, while Figure 4.8 presents a comparison between algorithm values and expert values. Results from the seven bare concrete bridge decks in the FHWA inventory are presented in each plot. Each plot also includes error bars at ±1σ based on error analysis calculations presented in Appendix D. These results indicate that the algorithm performs well relative to expert data interpretation, (as the overlapping error bars show), when cover depths are smaller than 9 cm, (based on measured values). For these same shallow cover depths, the trends in the algorithm cover depth closely match the expert interpretation.

Cover depths greater than 9 cm produce data with a low signal to noise ratio due to effects detailed in Section 4.2. The low signal to noise ratio of the data makes expert interpretation difficult, but some indications of reinforcing steel can be distinguished. These noise prone indications make up less than 25% of the reinforcing steel known to be in the top reinforcing steel mat. Never the less, the expert values for cover depth obtained from these interpretations compare favorably with measured values, (Figures 4.7 and 4.8, bridge decks R10 and R11). Algorithm values for these decks are not computed because a noise threshold criterion is exceeded for the data from these decks. This noise
threshold is defined by the expected frequency of phase alternations in the reconstructed PERES data in the layer the algorithm identifies as the top layer of reinforcing steel. If the data in this layer is traversed in either plan view direction, the phase should alternate between locations where reinforcing steel is present and locations where concrete is present. The minimum expected frequency of alternation, (corresponding to a deck with reinforcing steel spaced at 0.45 m, AASHTO, 1998), is 5.1 alternations per meter. If the frequency of phase alternation is below this threshold, the reinforcing steel is not being detected consistently. Therefore no further analysis should be conducted. A summary of the phase alternation results from bridge decks R7 through R13 is presented in Table 4.1.

<table>
<thead>
<tr>
<th>Bridge Deck</th>
<th>Phase changes/m</th>
</tr>
</thead>
<tbody>
<tr>
<td>R7</td>
<td>11.6</td>
</tr>
<tr>
<td>R8</td>
<td>10.1</td>
</tr>
<tr>
<td>R9</td>
<td>8.4</td>
</tr>
<tr>
<td>R10</td>
<td>4.7</td>
</tr>
<tr>
<td>R11</td>
<td>4.4</td>
</tr>
<tr>
<td>R12</td>
<td>6.6</td>
</tr>
<tr>
<td>R13</td>
<td>7.20</td>
</tr>
</tbody>
</table>

*Table 4.1 Phase changes per meter for bare concrete bridge deck sections.*

The phase alternation threshold only prevents analysis from continuing when reinforcing steel is not detected and does not preclude data from being analyzed at deep cover depths if reinforcing steel is detected.

After the cover depth of a bridge deck has been determined by the pattern recognition algorithm, the orientations and locations of the reinforcing steel and the probable locations of distress can be determined. Because this subsequent processing is dependent upon the accuracy of the cover depth measurement, (Section 3.3) the favorable comparisons between algorithm results and expert and measured values are particularly important.
The benefits of an accurate, automated process for determining the mean concrete cover depth of a bridge deck are clear for bridge inspectors and engineers. The cover depth is required for modeling chloride diffusion processes that lead to bridge deck corrosion. This type of modeling can be used in conjunction with other techniques to estimate the service life of a bridge deck. Cover depth is also an important consideration in making repair, rehabilitation and replacement decisions about bridge decks.

4.3.2 Reinforcing steel detection

Detecting the location and orientation of reinforcing steel in a bridge deck is important for bridge inspectors and the automated detection of distress in bridge decks. An example where bridge inspectors can use this information involves analysis of crack patterns on bridge deck surfaces (Mehta, 1993). The method the pattern recognition algorithm uses to determine the location and orientation of the reinforcing steel in the deck has been described in detail in Section 3.3.1. Results are presented in this section for bridge decks R13, R12, R9, R8 and R7. Graphical results from the reinforcing steel detection algorithm were already presented for bridge decks R7 and R13 in Section 3.3.1. Graphical results from the remaining deck data that was processed, and results from analysis using evaluation criteria, (defined in this section), are also presented.

A graphical comparison between the pattern recognition algorithm results and images from the data allow the performance of the algorithm to be assessed qualitatively. This algorithm performance is affected by a variety of factors, which will be discussed for each bridge deck. In the graphical comparison, red lines mark the locations of reinforcing steel along the length of each piece. These lines also indicate the orientation of the reinforcing steel.

The results from bridge deck R8 are presented graphically in Figures 4.9 and 4.10 and can be compared with the diagram of bridge deck R8 in Figure C6, Appendix C. Figures 4.9 and 4.10 present plan view layers of magnitude returns from PERES, where low magnitude reflections are represented in black and increasing magnitudes of reflections are represented by increasing gray scale colors up to white. These figures show good results for detecting vertically and horizontally oriented reinforcing steel, (which both produce strong reflections), respectively in the bridge deck. However, the
Figure 4.9 Detected reinforcing steel in the vertical direction in bridge deck R8.

Figure 4.10 Detected reinforcing steel in the horizontal direction in bridge deck R8.
performance is best for the reinforcing steel oriented in the vertical direction. This
difference in performance can be attributed to the shallow cover depth of the vertically
oriented reinforcing steel, (5.4 cm) relative to the cover depth of the reinforcing steel
oriented in the horizontal direction, (6.7 cm). The radar response can become distorted
for the deeper, horizontally oriented reinforcing steel because it has already been affected
by the shallower, vertically oriented reinforcing steel (Mast, 1993). Never the less, the
reinforcing steel locations and orientations are representative of the locations and
orientations of the steel in the deck.

Quantitative measurements of the algorithm performance are determined by three
performance values, which are determined separately for the shallow and deep
reinforcing steel in the deck. These performance values include the number of
reinforcing steel pieces detected, the length of steel accurately followed by the algorithm,
and the ratio of falsely detected reinforcing steel pieces to accurately detected reinforcing

<table>
<thead>
<tr>
<th>Bridge deck</th>
<th># of detected reinforcing steel pieces in deck</th>
<th>Steel length followed by algorithm (meters)</th>
<th>Ratio of false to accurate detections</th>
<th>Actual # of reinforcing steel pieces in deck</th>
<th>Actual steel length in deck (meters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R7</td>
<td>23</td>
<td>42.68</td>
<td>0.04</td>
<td>24</td>
<td>46.56</td>
</tr>
<tr>
<td>R8</td>
<td>22</td>
<td>41.36</td>
<td>0.00</td>
<td>23</td>
<td>43.24</td>
</tr>
<tr>
<td>R9</td>
<td>21</td>
<td>30.54</td>
<td>0.35</td>
<td>24</td>
<td>47.28</td>
</tr>
<tr>
<td>R12</td>
<td>10</td>
<td>20.08</td>
<td>0.81</td>
<td>6</td>
<td>21.9</td>
</tr>
<tr>
<td>R13</td>
<td>16</td>
<td>19.5</td>
<td>0.60</td>
<td>12</td>
<td>23.4</td>
</tr>
</tbody>
</table>

Table 4.2 Reinforcing steel detection algorithm performance for the top layer of the top reinforcing steel mat.

<table>
<thead>
<tr>
<th>Bridge Deck</th>
<th># of detected reinforcing steel pieces in deck</th>
<th>Steel length followed by algorithm (meters)</th>
<th>Ratio of false to accurate detections</th>
<th>Actual # of reinforcing steel pieces in deck</th>
<th>Actual steel length in deck (meters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R7</td>
<td>8</td>
<td>21.6</td>
<td>0.25</td>
<td>6</td>
<td>21.6</td>
</tr>
<tr>
<td>R8</td>
<td>11</td>
<td>19.8</td>
<td>0.91</td>
<td>6</td>
<td>21.6</td>
</tr>
<tr>
<td>R9</td>
<td>9</td>
<td>21.9</td>
<td>0.33</td>
<td>6</td>
<td>21.9</td>
</tr>
<tr>
<td>R12</td>
<td>18</td>
<td>15.73</td>
<td>1.30</td>
<td>12</td>
<td>24.36</td>
</tr>
<tr>
<td>R13</td>
<td>10</td>
<td>13.5</td>
<td>1.67</td>
<td>6</td>
<td>21.6</td>
</tr>
</tbody>
</table>

Table 4.3 Reinforcing steel detection algorithm performance for the bottom layer of the top reinforcing steel mat.
steel pieces. Comparable quantities are computed based on the bridge deck diagrams presented in Appendix C. Tables 4.2 and 4.3 summarize these results.

Tables 4.2 and 4.3 indicate some significant trends in the performance of the reinforcing steel detection algorithm. Based on these tables, the algorithm is effective for detecting reinforcing steel in the top layer of the top mat of reinforcing steel (Table 4.2). This is reflected in all three performance criteria. The number of reinforcing steel pieces detected by the algorithm is very similar to the actual number of reinforcing steel pieces for all of the deck sections analyzed, but particularly for deck sections R7 through R9. The length of steel that the algorithm accurately follows, (where steel length followed refers to the length of steel the algorithm detects that coincides with the true length of steel in the deck), is over 80% for all but one result, R9. For R9 the algorithm follows the reinforcing steel for 65% of its length for the top layer. The ratio of falsely detected reinforcing steel pieces to properly detected reinforcing steel pieces is generally low for the top layer of the reinforcing steel mat, but is higher for bridge decks R12 and R13 than the other three. These differences coincide with the fact that bridge decks R12 and R13 were both fabricated using the same concrete mix design and similar configuration at the FHWA NDE Validation Center, while bridge decks R7 through R9 were extracted from the same field bridge deck.

The performance of the reinforcing steel detection algorithm presented in Table 4.3 shows that reinforcing steel detection results are less consistent for the bottom layer of the top reinforcing steel mat than they were for the top layer of the top reinforcing steel mat. In particular, the ratio of false to accurate detections goes up significantly for most deck sections for the bottom layer of the reinforcing steel mat. This can be attributed to the distortions in the radar return from the bottom layer of the reinforcing steel mat caused by travel through the top layer of the reinforcing steel mat. However, it is notable that over 90% of the length of the reinforcing steel is accurately followed by the algorithm for bridge decks R7 through R9 in spite of these distortions. The performance is not as good for bridge decks R12 and R13, but over 62% of the length of the reinforcing steel is accurately followed by the algorithm for these two decks. Graphical results are presented for bridge decks R12 and R9 in Figures 4.11 and 4.12.
Figure 4.11 Detected reinforcing steel in the horizontal direction in bridge deck R12.

Figure 4.12 Detected reinforcing steel in the horizontal direction in bridge deck R9.
The reinforcing steel detection algorithm generally performs well for PERES data from bare concrete bridge decks. This is reflected in the performance values summarized in this section. Some effects of clutter and attenuation, (discussed in Section 4.2), are observed in the results, particularly when the reinforcing steel layer under analysis is positioned below another layer of reinforcing steel. The distortions in the reconstructed response created by this situation correlate with the increased number of errors that the algorithm makes in detecting reinforcing steel under these conditions. In spite of these errors, the reinforcing steel detection algorithm is effective when it is appropriately applied.

4.3.3 Distress detection

The distress detection algorithm described in Section 3.3.2 locates areas in a bridge deck with feature measurements that match known areas of detected distress in reconstructed PERES data. The pattern recognition method that the algorithm uses defines these areas as high probability locations of distress. The algorithm narrows the search to areas where distress is located by eliminating reinforcing steel locations from consideration and further narrows the search by defining the largest detected distress areas. The results from the algorithm show that the method is effective. Algorithm performance will be discussed by comparing results with the chain drag method (ASTM 4580-86, 1992), and the discussion will be informed by the performance of the current PERES prototype. Improvements on the current PERES prototype, and their ramifications for HERMES, will be discussed in Section 4.5 and Chapter 5 to examine approaches for future PERES and HERMES development for bridge deck inspection. Results from the distress detection algorithm will be discussed for bridge decks R7-R9, R12, and R13.

The distress detection results produced by the pattern recognition algorithm for bridge deck R13 have already been presented in the context of describing the distress detection algorithm, Section 3.3.3. These results showed that the algorithm detects distress areas in the two locations where distress was detected by PERES and manually located in the reconstructed data. The response to the 2.54 cm thick foam insert in the
left portion of the deck (Figure 3.20 circled in red) is detected in two parts, which are selected by the algorithm as two of the three largest contiguous areas of probable distress. The thirty largest areas of probable distress reveal a third area of the response to the 2.54 cm thick foam insert, three areas corresponding to the 0.6 cm thick insulation, (Figure 3.21 circled in red), and an area corresponding to the 0.1 mm polyethylene sheet. Remaining areas correspond to noise, clutter and errors attributable to the algorithm. The areas circled in green, which are in close proximity to the edge of the specimen, are more likely to result from noise and clutter than others because edge effects contribute significantly to responses in these areas. Figure 4.13 designates

![Figure 4.13 Thirty largest detected distress areas in bridge deck R13.](image)

detected distress areas that form localized groups in red circles in the bridge deck R13 algorithm results. Three of these six encircled areas correspond to a simulated distress in the deck, (Figure C1, Appendix C). Chain drag test results obtained by following ASTM D4580-86 produced responses in all four of the areas that contained simulated distress, (Figure B1, Appendix B). The chain drag result is superior in terms of detection accuracy, but disadvantages of the chain drag method and potential improvements to PERES, (and its HERMES counterpart), will be discussed further in section 4.5.
Results from the distress detection algorithm for bridge deck section R12 show that the algorithm detects a significant response, (Figure 4.14, circled in red) to distress among the three largest detected areas. The detection of distress in this area is confirmed by results from the ASTM D4580-86 chain drag test, (Figure B2, Appendix B). The distress detected by both methods corresponds to the location of a corrosion experiment designed to produce delamination distress (Section 2.2.3). Again, there are significant responses attributable to noise and clutter that prevent the algorithm from matching the chain drag test results. These performance issues will be addressed further in this section.

The results from deck sections R7 through R9, which are all from the same bridge deck, are presented in Figures 15 through 17. Of these three bridge deck sections, only R9 produced a response in the chain drag test. This response area was among the three largest detected by the pattern recognition algorithm, (circled in red in Figure 4.15). The three largest response areas detected by the pattern recognition algorithm for bridge decks R8 and R7 are presented in Figures 4.16 and 4.17. No positive responses were detected in bridge deck R8 or R7 using the chain drag test, (Figures B7 and B6, Appendix B). Based on the comparison to the standard test, the areas detected using the pattern recognition algorithm are false positives. These false positives could be produced by noise, clutter, and/or errors in the pattern recognition classification of the the PERES
Figure 4.15 Three largest detected distress areas in bridge deck section R9.

Figure 4.16 Three largest detected distress areas in bridge deck section R8.
data. The other possibility exists that these indications are meaningful and relate to distress in the deck that the current standard test does not detect. This argument is not well supported based on the results from bridge deck R13, (Section 2.3.1 and Figure B1, Appendix B), where the chain drag test detected two thin simulated distress areas that PERES was not able to detect.

The results from the comparison between the pattern recognition algorithm and the chain drag test indicate that the algorithm does detect distress areas, but two problems exist. The error rate of the classifier is estimated to be 19% based on a full leave one out analysis of the training data from bridge deck R13. An error rate on this order will contribute to false positive indications. The reinforcing steel detection algorithm will also have some bearing on false positive results, but even when reinforcing steel is detected over 94% of its length, (bridge deck R7), significant false positives are generated. The other contributing factor to false positives is the presence of noise and clutter in the data. Based on observations of the PERES data (Section 4.2) these two factors will contribute significantly to errors. This indicates that methods for reducing noise and clutter in PERES data should be considered to improve the pattern recognition algorithm results. These methods will be discussed in Section 4.5.
4.4 Analysis of field data

Field data was collected from the Van Buren Street Bridge using PERES, as described in Section 2.4. This data was analyzed using the pattern recognition algorithm described in Chapter 3, with a modification. The modification was required due to the geometry of the reinforcing steel mesh in the Van Buren Street bridge deck. In the Van Buren Street deck, the reinforcing steel were not arranged in orthogonal upper and lower layers in the top mat of reinforcing steel. Instead, the upper layer of the top reinforcing steel mat appeared to be skewed at a significant angle, approximately 104 degrees, relative to the lower layer of the top reinforcing steel mat (based on interpretation of Figures 2.22 and 2.23 which display apparent reinforcing steel indications). This was different from any of the sample bridge deck sections in the FHWA inventory (Appendix C) that were used for algorithm development. The sample deck sections had angles between reinforcing steel layers much closer to 90 degrees. The filters the algorithm uses to detect reinforcing steel work best for the 90 degree case, but a relatively straightforward conceptual change (which may also increase computation times significantly) can be made to detect reinforcing steel in mats that have layers at other angles.

For the Van Buren Street Bridge data, an appropriate filter choice is a modification to the template matching filter in Figure 3.8. The peak values in the filter follow a straight line in the Chapter 3 algorithm, but this filter will not detect reinforcing steel that are not oriented predominantly along this line, (this filter allows for only small angle variations from an expected orientation). Using filter designs where the peak values of the filter lie on lines at a variety of angles would allow the algorithm to test for the most significant response among a variety of angles. This optimized algorithm is likely to be developed in the future, but the concept can be shown in example analysis of the data from the Van Buren Street Bridge. A fixed angle of 104 degrees was selected between the reinforcing steel in the two layers of the top mat and the orientation of the filter was adjusted accordingly. The results in Figures 4.18 and 4.19 were obtained by the pattern recognition algorithm with this angle modification.
Figure 4.18 Reinforcing steel detection in the predominantly horizontal direction.

Figure 4.19 Reinforcing steel detection at 104 degrees relative to horizontal.
Figure 4.20 Thirty largest responses to the distress detection algorithm for PERES data collected from the Van Buren Street Bridge.

The performance of the reinforcing steel detection algorithm on the field data appears to be reasonable, but a quantitative assessment cannot be made due to the inability to confirm reinforcing steel locations by other means than the PERES data itself. Some apparent false calls appear in the data and some deviation from indications of reinforcing steel are present, but a significant proportion of the reinforcing steel are detected and followed accurately by the algorithm, based on indications in the data. A cover depth of 7.2 cm, determined by the algorithm, is within reasonable expected values. Expert analysis of the same PERES data yields a 6.0 cm cover depth. The modified filter design appears to work reasonably well, showing correlation with strong feature indications in the data, but more data will need to be analyzed in the future to draw any significant conclusions about it.

The distress detection algorithm was also implemented on the PERES data taken from the Van Buren Street Bridge. Expert interpretation of the data indicates poor correlation between chain drag testing and PERES results (strong indications in the PERES data appear in many locations where no distress is indicated by chain drag), so
evidence of algorithm effectiveness is highly speculative based on these results. Figure 4.20 presents the results from the algorithm, where white areas indicate probable distress. Red circled areas designate locations of significant chain drag responses.

4.5 **Recommendations for improving PERES to achieve better algorithm performance**

There are few improvements that can be made to the standard chain drag procedure, ASTM D 4580-86, to prevent lane or bridge closures when it is conducted. There is also no evidence that the chain drag procedure has any potential for analyzing asphalt covered bridge decks or providing objective measurements of bridge deck distress. A variety of improvements can be considered for PERES, (and its HERMES counterpart), to improve its distress detection accuracy, which may lead to better automated processing. These improvements may also lead to effective inspection techniques for asphalt covered bridge decks that would not require lane closures.

Important options to consider for improving the PERES system (and its HERMES counterpart when more testing for it has been completed) include increasing signal integration (averaging) to reduce noise, deconvolving raw PERES waveforms using the incident radar pulse, increasing the power in the incident radar pulse and/or modifying the antenna design to increase the bandwidth of the radar (improving its resolution).

Integrating (averaging) collected signals will reduce the signal to noise ratio by a factor of $1/n$ where $n$ is the number of signals integrated (Skolnik, 1980). Therefore, the signal to noise ratio improves with more integrations, but the improvement produced by more integration decreases as the number of integrations goes up. Currently PERES performs some signal integration (100 averages per waveform according to LLNL) but more could be done. Deconvolving raw PERES waveforms with the incident radar pulse involves filtering the signal to obtain the closest possible approximation to an impulse response. The idealized impulse response would result if the incident radar pulse were a unit impulse spike or Dirac delta function. For many ground penetrating radar applications, this deconvolved result is a significant improvement over raw data for feature detection. Increasing the input power in the incident radar pulse would improve the response by increasing the reflected response magnitude relative to noise. This would
reduce the effects of signal attenuation, but could also increase signal clutter, (which would be a negative side effect). Finally, the antenna design could be modified to increase the bandwidth of the incident radar pulse, which would increase the range resolution for PERES. The range resolution is given by the following relationship (Mast, 1994)

\[ \Delta R_z = \frac{v}{2B} \]  

(4.1)

where \( v \) is the propagation velocity of the radar pulse in the medium and \( B \) is the pulse bandwidth. This change would be very difficult and costly to implement, but it could have a major effect on the detection capabilities of the system, allowing smaller features to be detected. Disadvantages of this method would be increased attenuation at higher frequencies this broader bandwidth would include.

Each of these four approaches provides an opportunity to improve PERES and HERMES data, in terms of signal clutter, noise or attenuation. This improved data should allow the pattern recognition algorithm to perform much more effectively than it currently does and make real world analysis of this data useful. Second generation prototypes of the two systems are planned after this dissertation has been completed. If the performance of these two new systems can be improved adequately, providing equal or improved performance over chain drag survey methods, they will be an attractive testing option for state departments of transportation.