Using neural networks to analyse surface irregularities measured with holographic radar

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Abstract

Holographic radar is very sensitive to small irregularities in surface height [1][2]. Although this sensitivity was previously thought a disadvantage of holographic radar, recent measurements on dinosaur footprints [3] have shown that it can provide valuable information. A problem has been that the RASCAN 4 holographic radar system used in this work has provided separate signals at 5 different frequencies between say 3.6 and 4.0 GHz and at both parallel and perpendicular polarisations, each of which gives a distinct signal as a function of surface height and other variable. These signals are complicated to calculate but can be measured using a sloping surface of known height and other properties. Here neural networks are trained on a gently sloping surface of smooth sand to recognise the RASCAN signals as a function of surface height. In a testing mode, the neural networks should be able to use all the recorded signals to distinguish small differences in surface height as a function of position.

1. Introduction

The measurements were recorded in the garden of the Information Engineering Department of the University of Florence in Italy. Two parallel planks of wood provided a path for the robotic scanner [4] over sloping sand whose depth varied uniformly between 150 mm and zero over a 1300mm path, ending with a flat region of some 500mm of constant depth. The RASCAN 4 radar head was mounted on a transverse bracket which moved the radar head at constant speed backwards and forwards across the slope over about a 300mm span. The RASCAN was set to record 9 frequencies equally spaced between 3.6 and 4.0 GHz at each polarisation. The different frequencies were therefore measured sequentially at slightly different positions up the slope (x) and across the slope (y). The speed of the robot up the slope was 1 mm/sec, and speed of the data collection was such that each frequency was spaced by only around 0.22mm up the slope (x). However each of the 9 frequencies was recorded at the considerable distance of 12 mm across

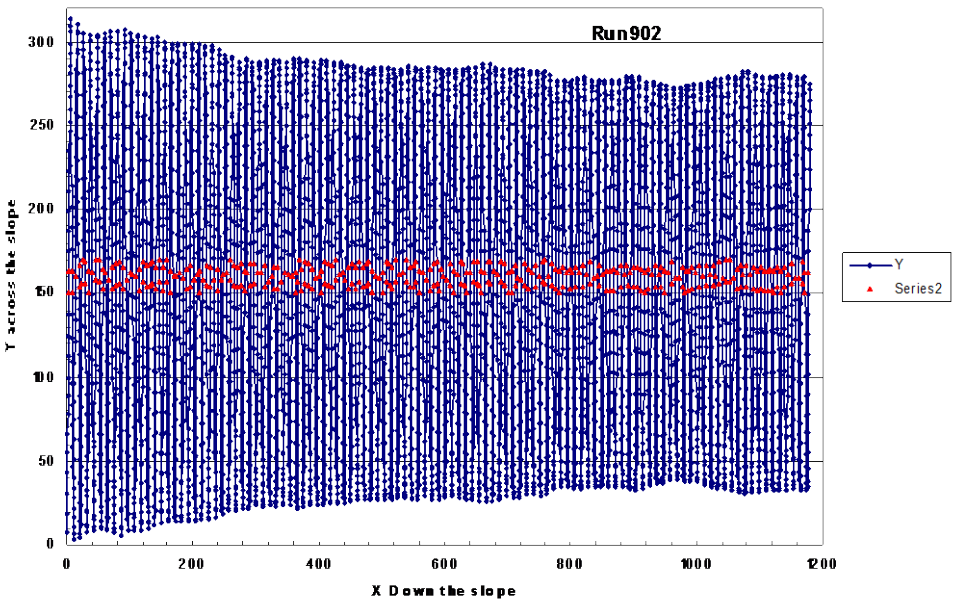

Figure 1: The scanning path of the RASCAN head (blue). This moved in a zigzag path up the slope from left to right in the figure. The red points show a 20mm band of points that could be used for training.

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the slope (y) so that the resolution of the measurements was much degraded across the slope, although still comparable with the RASCAN resolution of order 10mm. Each complete scan took around 20 minutes.

The 9 individual frequencies could be collected along the 20mm band shown in red in Figure 1 and displayed as a function of depth. This varied from 120 mm at the start of the scan to zero at 960mm along the scan, after which the depth stayed constant for the remaining 250mm of the scan. Figure 2 shows a display of the 9 parallel signals as a function of depth. It is seen that each frequency is slightly different. Some of the frequencies (say the one coloured dark blue) show an oscillation between alternate points which may be caused by a slight change in level across the scan direction.

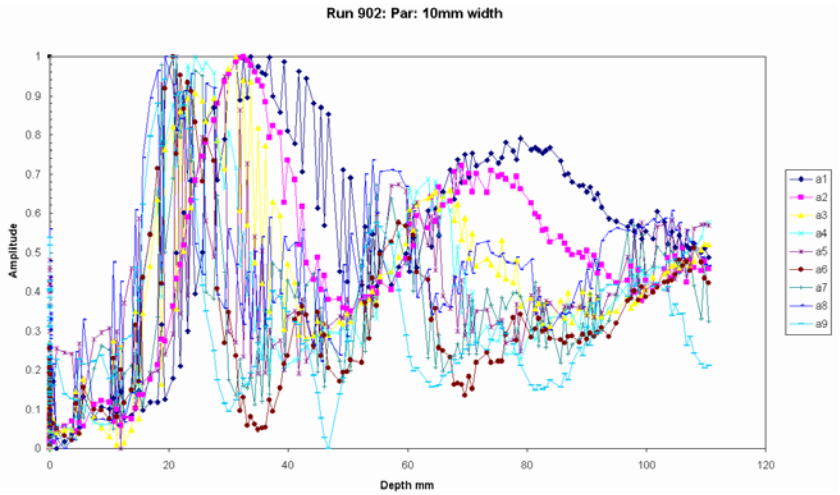

Figure 2: The 9 parallel polarisation signals displayed as a function of depth in mm.

2. The neural net training

The parallel polarisation amplitude signals at the 9 different frequencies shown in Figure 2 were used as the inputs to a neural network training scheme trained with the target being the depth (divided by 120 to cover the range 0 to 1). The amplitudes were also scaled to cover the range 0 to 1 as defined in the input data provided by the scanner. The standard Rumelhart Multi-Layer-Perceptron method was used with the training data divided into 75% training and 25% testing. The training is carried out in only a few seconds as shown in figure 3. After this the agreement between the actual depths, and the depths predicted by the network may be plotted in a scatter plot for both training and test data as shown in figure 4. The scatter plot shows a good degree of fit from both training and testing points. This particular plot is for a network with 7 hidden units. This number defines the number of degrees of freedom in the fitting process. Too few hidden units and neither training nor test points will be fitted. With too many hidden units the training data will be studiously fitted but the test data may be poorly fitted. A plot of the training and test residuals as shown in figure 6 is able to define the optimal number of hidden units. Having performed this optimisation, all the available data from the 10mm wide strip down the centre of the scan may be used for training, to provide a set of network weights, which may be used to predict depths from any other part of the scan or of similar scans. For example the scatter plot for the much larger dataset 200mm wide covering all but the far edges of the sloping sand scan: the 60mm or so at either end was affected by the edges of the sloping sand pit, and was therefore omitted.

3. Results

The final step is to convert the depth prediction results into a grey scale picture of the trench showing the change of depth along its length. Another process that may now be performed is to subtract off a fitted slope that will be calculated to make the trench level, and so best reveal any irregularities. This is done by plotting the height down the central 100mm strip at the centre as a function of the position (x) along the scan. This is readily performed as shown in figure 6 and the corrected depths may be plotted for the full width of the scan as in figure 5 in gray scale to provide a corrected depth scan as in Figure 7.

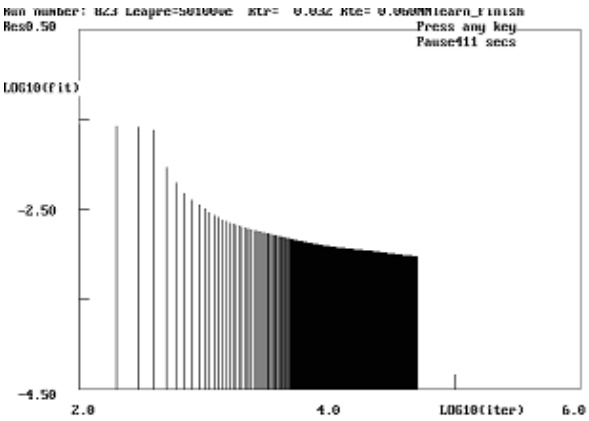

Figure 3: The training residual reducing over 10000 iterations of the neural net training process.

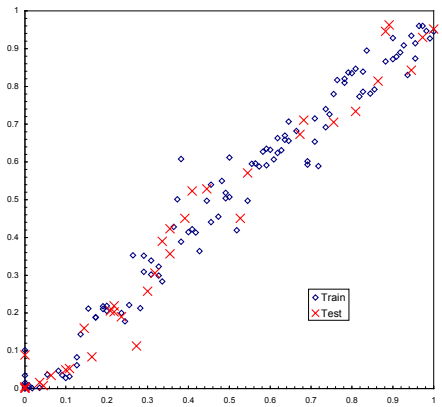

Figure 4: The actual depth for each of the example measurements (x) plotted against the predicted depth (y) for training and testing points.

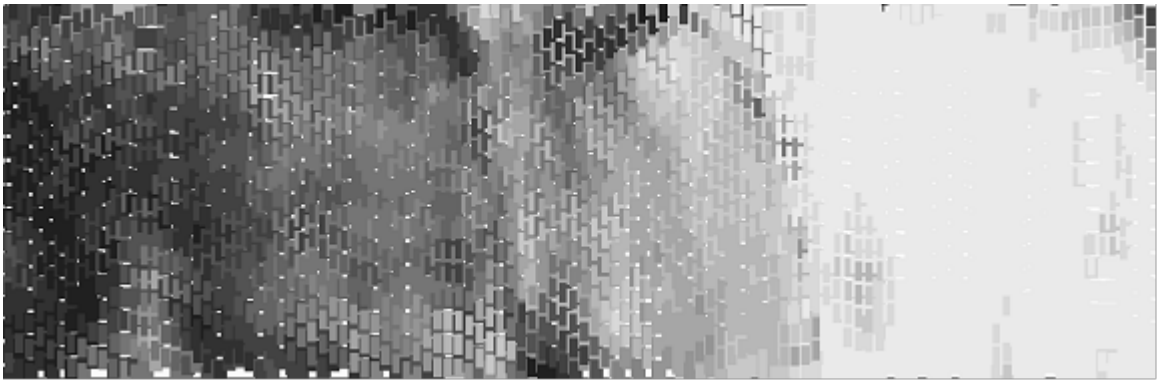

Figure 5: A grey scale image of the sloping sand trench. The dark area to the left is some 110mm lower than the generally white flat area to the right. The oblong pixels of the data points are clearly seen indicating that the resolution along the slope is much better than it is across the slope. Larger height corresponds to darker pixel color.

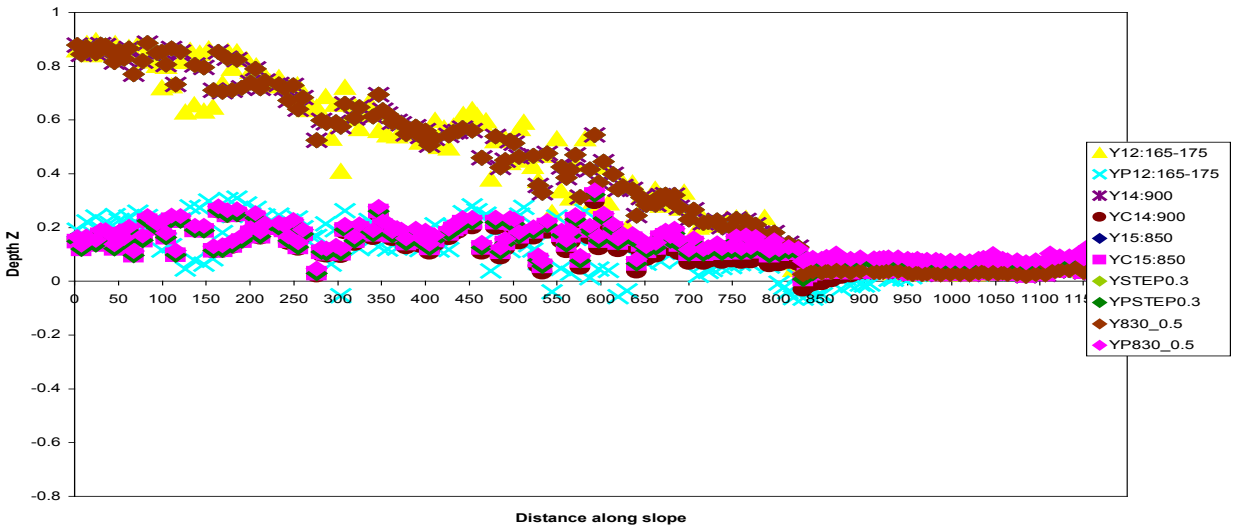

Figure 6: The actual depth z of the sand as determined by the neural network output (brown and yellow) compared with the corrected values after a linear slope has been subtracted (purple and blue)

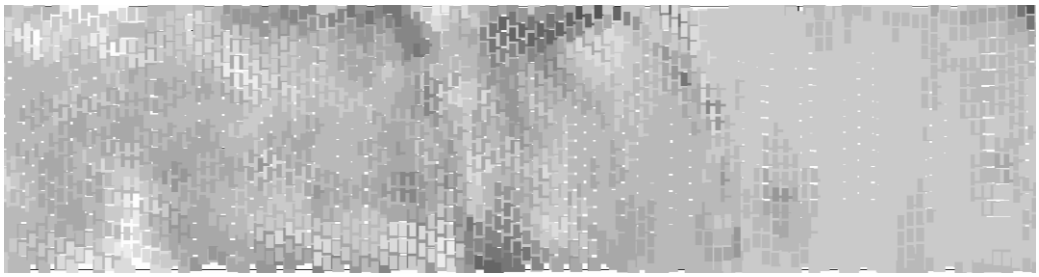

Figure 7: The grey scale display of the corrected (flattened slope) data

5. Conclusion

A high spatial resolution scanning method based on a robotic platform has been employed to scan an inclined surface with an holographic radar. In order to use the holographic radar scanner on irregular surfaces, the effects of the distance variation of the surface from the antenna can be removed by different methods. Full three dimensional holographic data reconstruction can be applied if the travel path in air is known with enough accuracy for each antenna position; this method requires quite a lot of computational efforts especially for inspection of large surfaces with high frequency holographic radar (>4GHz). The paper shows a different method based on neural network training on different data sets obtained with different discrete frequencies. The results obtained show that an inclined surface of sand test bed can be corrected (flattened slope) with small amplitude variations. This allows to investigate this method for the visualization of shallow buried objects present in both flat and inclined areas. The method presented here will be tested for landmines detection [5] and the search of hidden shallow dinosaurs footprints[3].

6. Acknowledgments

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7. References

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