Millimeter-Wave Active Imaging Using Neural Networks for Signal Processing

Ken-ichi Watabe, Koji Shimizu, Masahide Yoneyama, *Senior Member, IEEE*, and Koji Mizuno, *Fellow, IEEE*

***Abstract*—A neural network has been successfully implemented in an active-mode millimeter-wave (60 GHz) imaging system with a Yagi–Uda antenna array in order to recognize objects and reconstruct images that appear distorted under coherent millimeter-wave illumination. With 10 $\times$ 10 sampling points and five teaching trials, a recognition rate of 98% has been obtained for ten dissimilar alphabetical letters used as objects. The success rate of reconstruction of distorted millimeter-wave images was 80% when five dissimilar letters were used for the reconstruction. The recognition rate after changing the spatial resolution of the optical system and sampling interval of the image is also discussed.**

***Index Terms*—Active-mode millimeter-wave imaging, image reconstruction, imaging array, neural network, object recognition.**

I. Introduction

MILLIMETER-WAVE imaging can be used to obtain information through clouds, smoke, dust, and other obstructions that render visible and infrared (IR) systems ineffective. It also has applications in plasma diagnostics, atmospheric and planetary remote sensing, automotive collision-avoidance radar, etc. [1]–[3].

Millimeter-wave imaging can be either active or passive mode. Active-mode millimeter-wave imaging has a higher signal-to-noise ratio than passive-mode imaging, but the active-mode images are distorted by speckle and/or glint under coherent illumination [4]. Moreover, millimeter-wave imaging cannot offer spatial resolution better than visible or IR imaging for a given optical aperture size. In some cases, these distorted images cannot be recognized and, therefore, it is necessary to improve the recognition rate. Various active-mode microwave and millimeter-wave imaging techniques and their image-reconstruction algorithms for target identification have been documented by several authors [2], [5]–[7]. However, there is no report of a neural network [8] being used in signal processing for target identification in a camera-mode active-mode millimeter-wave imaging system using an imaging array [9], which would make real-time operation possible. Signal-processing technology using a neural network has applications in pattern recognition [10], speech recognition, control of robots, tomographic microwave imaging [5], and ultrasonic imaging [11]. In image processing, the recognition rate can be rapidly raised [10], [11].

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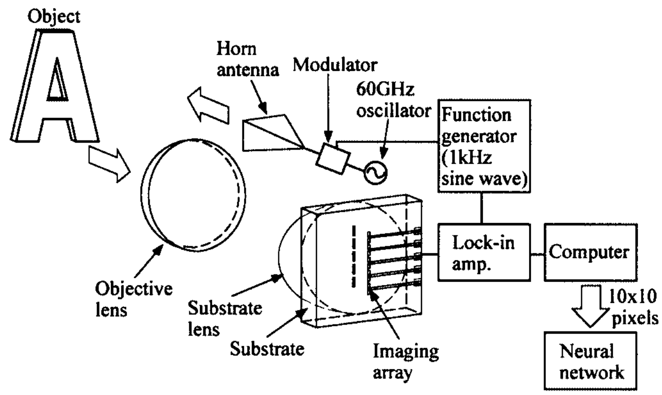

Fig. 1. Millimeter-wave active imaging system.

This paper describes a 60-GHz active imaging radar, which uses a Yagi–Uda antenna array that we developed. The imaging radar incorporates multilayered feedforward neural-network signal processing to recognize objects and reconstruct images distorted under coherent illumination. It is shown that a good associative memory can be constructed using a Hopfield neural network; nevertheless, we have adopted the multilayered feedforward neural network because of the following reasons. The Hopfield neural network has an upper limit of the number of patterns that can be recalled [12]. The limit of the number of stored patterns depends on the number of neurons used in the network. Increasing the number of neurons leads to increasing the learning time for the network. Moreover, the real-time operation to recall the stored pattern is impossible because some extent of operating time is necessary to relieve the network energy. Considering some practical applications, the real-time performance is quite important. From the above reasons, we preferred the multilayered feedforward network for our research means. The previous signal processing [13] using the neural network in our imaging system was limited to object recognition. To reconstruct images, we implemented the neural network for image reconstruction. Moreover, we examined the recognition rate by changing the spatial resolution of the optical system and the sampling interval of the image.

II. Millimeter-Wave Active Imaging System

The experimental arrangement used for the millimeter-wave imaging system is shown in Fig. 1. A horn antenna was used to illuminate an object with a linearly polarized coherent 60-GHz signal, with the signal amplitude modulated to allow phase-sensitive detection. Millimeter waves scattered by the object were

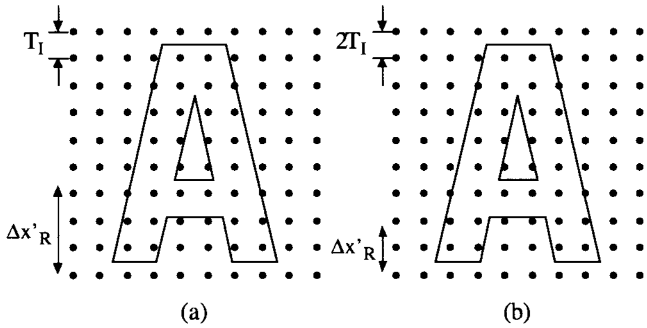

Fig. 2. Spatial resolution of the optical system and the sampling interval of the image for the example of the letter A. (a) The experiment with the effective F-number of 1.68. (b) The experiment with the effective F-number of 0.84. Black dots represent sensors. T_I corresponds to the interval between sensors, which is determined by the sampling theorem for obtaining a diffraction-limited image. $\Delta x'_R$ corresponds to the spatial resolution of the optical system on the image plane.

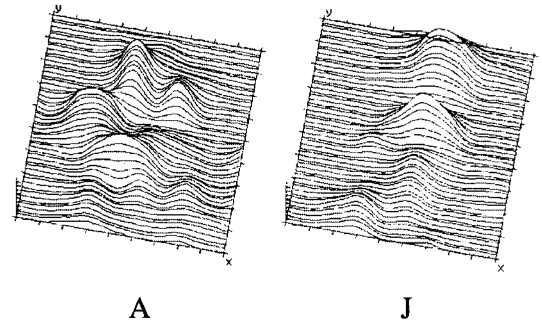

Fig. 3. Millimeter-wave images for the letters A and J.

focused by two dielectric lenses to construct an image. The optical system consisted of an objective lens (TPX, $\varepsilon_r = 2.13$) and a hemispherical substrate lens [14], [15]. A ten-sensor one-dimensional imaging array [9], [16] was positioned in the focal plane, on the backside of the substrate lens, and two-dimensional images of 10 × 10 pixels were composed by mechanically scanning the array in the other dimension. The imaging array consisted of ten two-element Yagi–Uda antennas, each with beam-lead Schottky-diode detectors (SANYO SBL-804). The radiator elements were half-wave resonant dipoles on a thin plate of PTFE/glass with $\varepsilon_r = 2.17$, which is almost the same dielectric constant as that of TPX, and the diodes were integrated as detection elements at the feed point of each radiator. The director elements were on the other side of the plate. The antenna element dimensions were optimized for matching the impedance to the diodes and beam pattern to the optical system. The interval between sensors was 0.84λ, where $\lambda = \lambda_0/n$. Here, λ_0 is the vacuum wavelength and n is the refractive index of the TPX substrate lens.

III. Millimeter-Wave Images

Alphabetical letters made of aluminum foil were used as test objects for evaluating the imaging system. The size of the geometrical image on the image plane is as much as eight times the interval between sensors in the vertical direction. The millimeter-wave images were experimentally obtained under the following two sets of conditions to study the spatial resolution of the optical system and sampling intervals for images:

a) the effective F-number is 1.68, and the sampling interval T_I is determined by the sampling theorem for obtaining a diffraction-limited image;
b) the effective F-number is 0.84, and the sampling interval is twice the interval determined by the sampling theorem (Fig. 2).

The effective F-number can be written as [15], [17]

$$F_{\text{eff}} = \frac{1}{2\sin\theta} \tag{1}$$

where θ is half the angle subtended by the exit pupil when the distance between the object and the optical system is finite. The spatial resolution on the image plane was calculated using Rayleigh's criterion for resolution [18] as follows:

$$\Delta x'_R = 1.63 F_{\text{eff}} \lambda \tag{2}$$

where $\Delta x'_R$ is the spatial resolution of the intensity image in case of coherent illumination, where it is assumed that two object points are illuminated by the same phase. The magnification of the optical system was 0.26 in Case a) and 0.094 in Case b). Therefore, the electrical size of the target in the vertical direction was $17.5\lambda_0$ in Case a) and $48.8\lambda_0$ in Case b). The reason why the electrical size was different is that we changed the optical system while using the same imaging array under both conditions. In Case b), the spatial resolution on the image plane is twice as good as that for Case a). The gap at the bottom of the letter A will, for example, not be resolved by the optical system in Case a), although it will be resolved in Case b). Examples of experimentally obtained images for the letters A and J in Case b) are shown in Fig. 3. The images represent the power distribution of the scattered signals and are strongly distorted, mainly because of speckle and/or glint resulting from the coherent illumination.

IV. Object Recognition

To recognize these images, we used a back-propagation model neural network [19], [20] as a signal processor. The network configuration for object recognition, which consisted of 10 × 10 input units, 60 hidden units, and 26 output units, is shown in Fig. 4. It was implement using a workstation (110-MHz Sparc Station 5), and the number of learning was set to 10 000. The recognition rate was studied as a function of the number of "teaching-data" required, when ten dissimilar letters (A, H, J, L, O, P, S, T, V, and Z) were used as the objects. In this experiment, nine sets of image data were collected for each letter by randomly changing the incident angle from the optical axis of the millimeter-wave to the object from 30° to 60°. Although the choice of data to be used for teaching is important, teaching-data was selected and taught to the network as follows.

1) An arbitrary data set was first selected from the nine sets of image data as teaching data and the other eight sets were used as test data, and the recognition experiments were conducted.
2) The set of test data with a particularly poor recognition rate was added to teaching data and the other seven sets

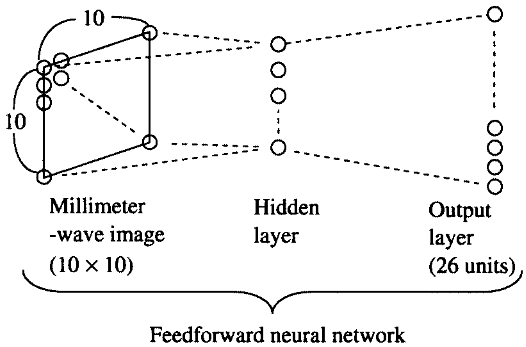

Fig. 4. Configuration of the neural network for object recognition. It consisted of 10 × 10 input units, 60 hidden units, and 26 output units. It was implement using a workstation (110-MHz Sparc Station 5), and the number of learning was set to 10 000.

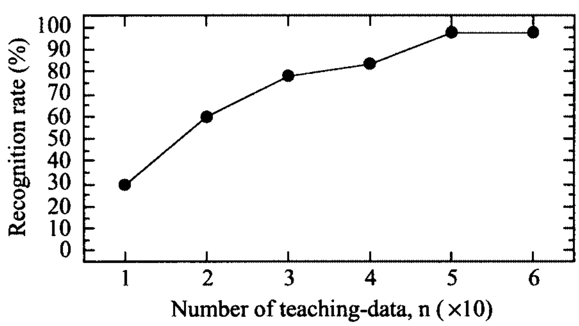

Fig. 5. Recognition rate as a function of teaching data in Case b) in Fig. 2. Ten dissimilar letters were used as objects.

were used as the test data, and the recognition experiments were conducted.

3) By repeating the above procedure, teaching-data sets were increased to six.

In Case b) in Fig. 2, the resulting recognition rate in this first case for one set of teaching data was very poor (30%) since a varying degree of distortion had not yet been taught to the network. By repeating the above process, the recognition rate was improved, as shown in Fig. 5. A high recognition rate of 98% was obtained using data from five teaching trials for each letter, which shows that neural network signal processing is very suitable for millimeter-wave active imaging. In this case, in the teaching mode, after learning 10 000 times, the squared error function [11] became smaller than 0.01 for every pattern. In Case a) in Fig. 2, however, the recognition rate remained very poor, although this process was repeated and, in the teaching mode, after learning 10 000 times, the squared error function did not converge at all. This implies that the objects are well recognized even though the sensors are roughly spaced at twice the interval determined by the sampling theorem when the resolution of the optical system is sufficiently high, but are not recognized when the sensors are spaced at the interval determined by the sampling theorem when the resolution of optical system is not sufficiently high.

In the teaching mode in Case b), it took less than 2 min to calculate one letter. On the other hand, processing for recognition was a real-time operation.

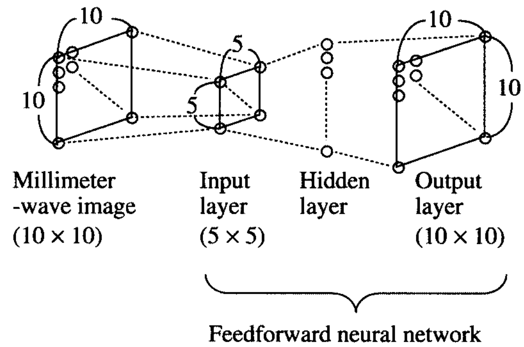

Fig. 6. Configuration of the neural network for object image reconstruction. It consisted of 5 × 5 input units, 30 hidden units, and 10 × 10 output units. This network was implement using a workstation (110-MHz Sparc Station 5). The number of units of the input layer was reduced to 25, which was computed by averaging values for the neighboring four pixels (2 × 2 pixels) of the millimeter-wave image to avoid having a neural network that is too large.

V. Image Reconstruction

The neural network for image reconstruction reconstructs the object's shape. The network configuration for image reconstruction, which consisted of 5 × 5 input units, 30 hidden units, and 10 × 10 output units, is shown in Fig. 6. This network was also implement using a workstation (110-MHz Sparc Station 5). Generally, the number of units of the input layer should also be $10 \times 10 = 100$, but to avoid having a neural network that is too large, we reduced the number of units of this layer as follows. The average values for the neighboring four pixels (2 × 2 pixels) of the millimeter-wave image were computed. As the total pixel number of millimeter-wave images is 100, the number of averaged values is 25. These averaged values were used as input data to the neural network. Therefore, the number of units of the input layer could be reduced to 25.

In this experiment, image data were only collected in Case b) because of the results of the object recognition. Five letters (A–E) were used as objects, and nine sets of image data were collected for each letter by the same method, as described in Section IV. From the nine sets, three arbitrary sets were used as the teaching data and the rest were used as the test data. As we used two-dimensional objects in the experiment, the teaching data for the output pattern had to be binary values. These teaching data consist of 10 × 10 pixels and were made according to their object's shape.

Fig. 7 shows examples of successful reconstruction and incorrect reconstruction for the letter B and shows samples of distorted millimeter-wave images and their reconstructed images. For clarity, the images shown in this figure have been composed of 60 × 60 pixels by inserting five pixels between two original neighboring pixels and interpolating linearly. Table I shows a confusion matrix obtained from the experimental results for five letters. An average reconstruction rate of 80% was obtained. The resulting reconstruction rate for the letters B and C were poor (50%) since they were easily confused with E when five letters (A–E) were used. This implies that even reconstruction rates for the same letter change when different combinations of letters are used as the teaching data.

In the teaching mode, it took less than 1 min to calculate one letter, and after learning 10 000 times, the squared error function

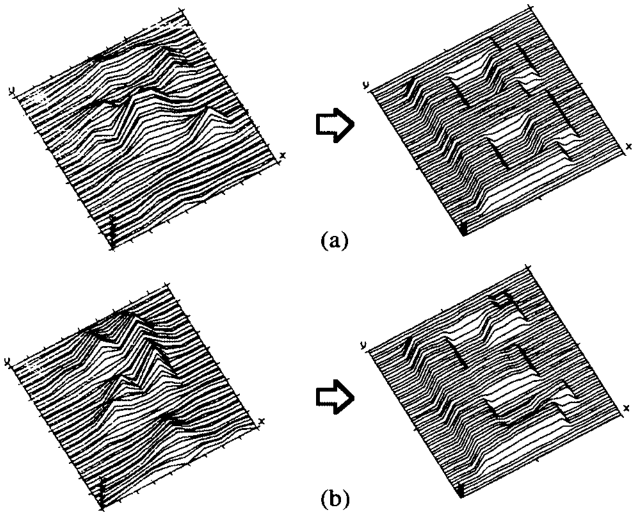

Fig. 7. Reconstructions of millimeter-wave images of the letter "B." (a) Successful example. (b) Unsuccessful example, which yields a different letter "E."

TABLE I
RECONSTRUCTION RATE FOR FIVE LETTERS. THE NUMBER OF TEACHING-DATA SETS WAS THREE AND THE NUMBER OF TEST-DATA SETS WAS SIX IN ALL CASES

Input \ Output	A	B	C	D	E	*	%
A	6						100%
B		3			1	2	50%
C			3		1	2	50%
D				6			100%
E					6		100%

became smaller than 0.01 for every pattern. On the other hand, processing for recognition was a real-time operation.

VI. CONCLUSION

We successfully implemented a neural network in an active-mode millimeter-wave (60 GHz) imaging system with a Yagi–Uda antenna array in order to recognize objects and reconstruct images that appear distorted under coherent millimeter-wave illumination. Two sets of experimental results were obtained by changing the spatial resolution of the optical system and the sampling intervals for images. The objects were recognized accurately even though the sensors were spaced at roughly twice the interval determined by the sampling theorem when the resolution of the optical system was sufficiently high, but not recognized when the sensors were spaced at the interval determined by the sampling theorem when the resolution of the optical system was not sufficiently high. When the sensors were spaced at twice the interval determined by the sampling theorem and the resolution of the optical system was sufficiently high, a recognition rate of 98% was obtained for ten dissimilar letters used as objects with five teaching trials. The success rate for reconstruction of distorted millimeter-wave images of five different letters was 80%. This implies that the millimeter-wave images, which appear to be heavily distorted, in fact have certain features that follow certain laws, and that neural network signal processing can be used to recognize or reconstruct these active-mode millimeter-wave images. This method of signal processing may be applied to recognition and reconstruction of millimeter-wave images that are distorted, provided the resolution of the optical system is good enough.

Planned future work includes changing the number of teaching data and increasing the number of alphabetical letters in experiments on image reconstruction.

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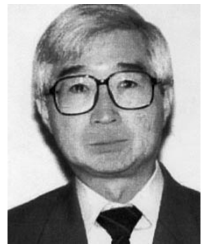

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