MICROWAVE VISION FOR ROBOTS

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ARTIFICIAL NEURAL NETWORK – MICROWAVE VISION

Microwave Vision (MV), a concept originally developed in 1985 [1] could play a significant role in the solution to robotic vision problems. Originally our Microwave Vision concept was based on a pattern matching approach employing computer based stored replica correlation processing. Artificial Neural Network (ANN) processor technology offers an attractive alternative to the correlation processing approach, namely the ability to learn and to adapt to changing environments. This paper describes the Microwave Vision concept, some initial ANN-MV experiments, and the design of an ANN-MV system that has led to a second patent disclosure in the robotic vision field[2].

MICROWAVE VISION CONCEPT

Microwave Vision is similar to a bistatic radar system: Electromagnetic waves are radiated into the observation space, the reflected signals are received and processed to yield range and bearing to the object. Typically radars radiate pulsed RF signals. MV is instead based on the measurement and processing of a distinctive set of spectral lines. Similar to some high resolution radars, MV identifies the object by the spectral character of the reflected returns. MV differs from bistatic radar systems in two important aspects: 1) MV signals span much larger radio frequency bandwidths and 2) MV systems operate in the "near field" of the object. Precise position information and accurate object identification is achievable when operating at short ranges over very wide frequency ranges.

The spectra returned from different objects become more distinct by using an illumination spectrum that spans the natural electromagnetic resonance of these objects. For example, identification of a 10 cm tall object is based on signals containing frequencies in the neighborhood of 3 GHz. Figures 1, 2 and 3 demonstrate a simple version of the MV concept. One dipole transmits and the second receives a

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Figure 1. Six cm Tall Equiangular Wedge and Dipole Array Geometry

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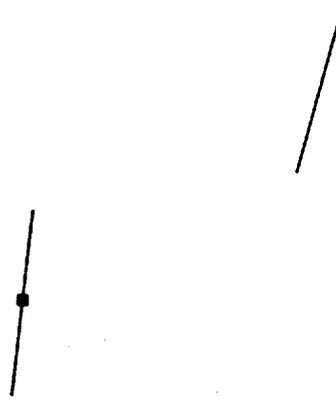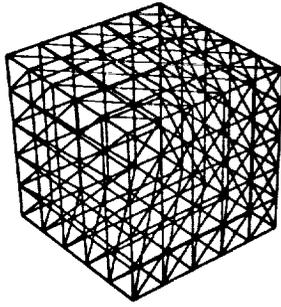
Figure 2. Six cm Cube and Dipole Array Geometry

FREQUENCY (MHz)

9-93-006
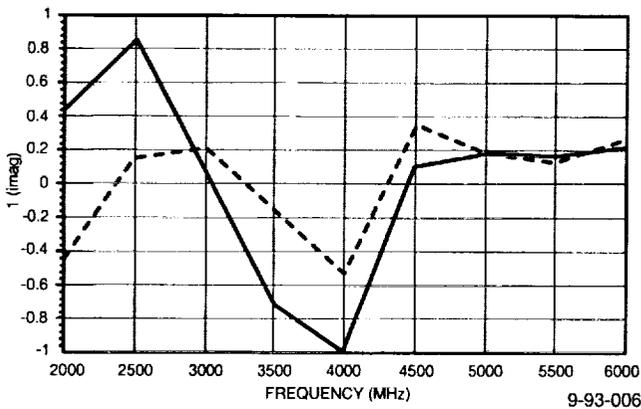
Figure 3(a). Receive Current Level (Imaginary
Part) Cube (solid line), Wedge (dashed line)

FREQUENCY (MHz)

9-93-007
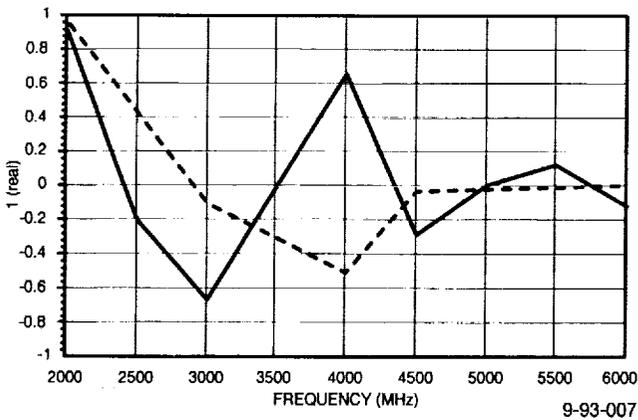
Figure 3(b). Receive Current Level (Real
Part) Cube (solid line), Wedge (dashed line)

set of 10 spectral frequencies, evenly distributed between 2 GHz and 6 GHz. The reflected signals, as measured by the current on the second dipole, are strongly dependent on the particular object illuminated as shown by comparing the spectrums shown in Figure 3. Here, real and imaginary spectral components of the RF signal, reflected from the 6 cm tall equiangular wedge, and those reflected from the 6 cm cube are displayed. The two objects are clearly distinguishable through the contrast of their respective spectral returns.

The original MV concept was based on the correlation of measured spectral patterns with patterns "measured" from previous calibrations. During these early experiments the Correlation Coefficient R was recorded as a function of the water depth in a coffee cup. When the cup was full, the correlation to a previously recorded full cup spectral pattern was equal to unity. As the water depth was reduced, the spectrum responses changed, reducing the correlation value from unity to a minimum of 0.25 when the cup was completely empty. This simple experiment

clearly demonstrated that the MV correlation process can yield information that is difficult to acquire with purely optical systems. The original correlation process was effective, but the trainable ANN processing technique has many additional advantages.

Artificial neural networks are ideal for use in an MV system, because unlike a computer or signal processor they are not programmed in the classical sense, but are instead trained using in this case, the MV spectrum measurements as the training stimulii.

ANN-MV PROOF OF CONCEPT SYSTEM

Our experimental ANN-MV system, shown in Figure 4, was trained to guide a simple robotic hand to a position that encloses the object. This system, used transmit and receive antennas mounted on the robotic hand to excite and receive reflected signals from simple objects. A center Vivaldi antenna sequentially transmitted a set of discrete signals that were received by the two outer antennas that form a pair of fingers on the robotic hand. Two sets of measurements are needed to resolve the signals reflected from the illuminated object. Each measurement set is

recorded when the HP measurement channel is sequentially connected to one of the outer antennas. Object location measurements contain the sum of two sets of spectrums, the spectrum of the signal directly transmitted from antenna to antenna plus the desired signal spectrum that represents the signal radiated to the object of interest and reflected into an outer antenna. The reflected signal spectrum of interest is obtained by subtracting an initially measured baseline spectrum, a spectrum which was recorded when the object was absent. The resultant reflected signal is then inserted into the first layer of the ANN system.

Artificial neural network processing, as used in ANN-MV, is based on training the connecting weights between an input layer, a hidden layer and the output layer of an i80170 Intel Processor. Other ANN processing algorithms or processing techniques could have been investigated, but the availability of the Intel Chip and the relative ease of back propagation training [3] led to early experiments using the unit.

Many ANN based system applications are plagued with preprocessing problems associated with the generation of input vectors significant to
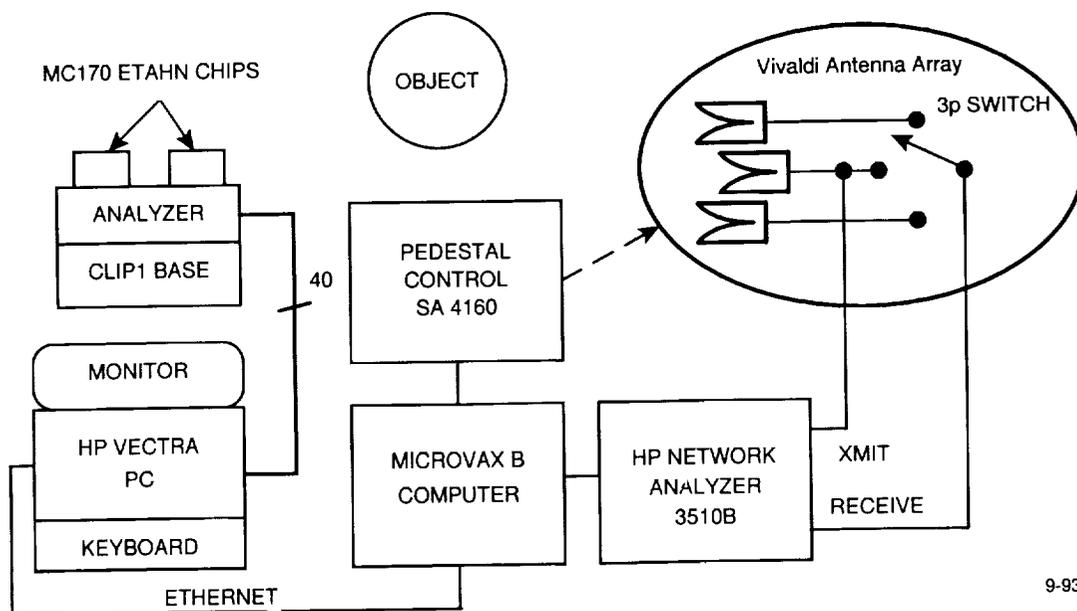
Figure 4. Schematic of Experimental ANN-MV System

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the resolution problem. Microwave Vision affords a natural set of input vectors, i.e., those real and imaginary parts of the spectral lines reflected from the object and recorded at the receive antennas, as shown in Figure 3. As mentioned previously, the spectral lines should encompass the natural electromagnetic resonant frequency of the unknown objects.

The signals are weighted and summed at both the middle ANN layer and the output ANN layer. Rudimentary training process would be the task of forcing the output of an artificial output neuron (K) to be high when the input vectors correspond to reflections from object (K) but low for reflections from all other objects. This particular problem is a relatively easy ANN-MV task for many categories of objects. The robotic vision problem is significantly more complex since the robot needs to also measure the location and orientation of the object.

Our original ANN-MV task was to locate and move the hand to a soft drink can that was randomly located within a 50 cm radius/90° quadrant field of view. Most of the experiments were conducted by connecting the input layer containing 32 artificial neurons to middle layer consisting of 32 neurons and an output layer consisting of two neurons. The back propagation training algorithm was tasked to generate two outputs having patterns given by:

$$\overline{Y}_{out}(1) = Range * Cos(\theta)$$

$$\overline{Y}_{out}(2) = Range * Sin(\theta) \qquad \text{EQ-1}$$

Guidance to the hand was then given by a pair of simple calculations based on these two outputs. A complete set of input training vectors was obtained by sequentially positioning the can to 77 locations, every 15 degrees from -45 to +45 and 10 cm to 30 cm in 2 cm increments. At each location an (I) and a (Q) value was recorded for each of 16 frequencies between 2 GHz and 4 GHz. Exceedingly long, several hours, on chip

training times were observed. Large robotic hand guidance errors were also measured unless the can was located very close to a training location. Subsequent tests showed that the input vectors changed markedly for small changes in can locations. These changes can be attributed to the phase rate of change with respect to centimeter changes in distance. At 3 GHz, a 2.5 cm range increase creates a two-way path change of 5 cm equivalent to 180 electrical degrees. This change dictates a training set based on differential ranges of approximate 0.5 cm.

Experiments with the initial ANN-MV processing technique demonstrated significant deficiencies in object location accuracies. These deficiencies were primarily caused by large input vector phase changes associated with distance changes normal to equal range contours, relative to the transmitter and receiver phase centers. This led to a system design that exploits "this" effect by sequentially preprocessing the input data as it is inserted into the ANN input layer. Initial investigations show that this preprocessing concept reduces the training time and sharply reduces residual training errors.

Object location algorithms are based on the intersection of equal time delay, elliptical contours. The transmit and right finger receive antenna are located at the foci of one set of elliptical contours, the transmit and left finger receive antenna are at the foci of the second set of elliptical contours. Figure 5 shows a pair of contours for two time delay paths from the center Vivaldi antenna to the Vivaldi antenna located on the right side of the hand. Each contour represents a particular time delay and therefore all object training positions along this contour can be operated on by the same set of phase unwrapping vectors. This phase unwrapping concept is the frequency equivalent of time domain range gating which is so effective in conventional radar systems.

RIGHT
VIVALDI

CENTER
VIVALDI

LEFT
VIVALDI
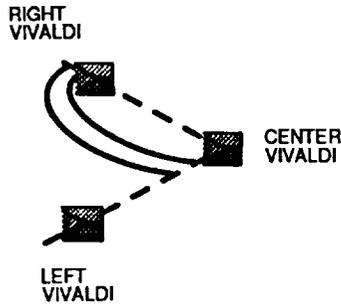
Figure 5. ANN-MV Elliptical Contours

Robotic control is based on two ANN Intel processors. The first processor receives inputs based on measurements between center antenna and the right finger antenna. Inputs to the second processor are based on center antenna to left finger antenna measurements. Each ANN processor performs identical operations which is to calculate and identify the contour having the highest probability of containing the object.

A set of 32 complex spectral responses are calculated by measuring the signal transmitted from the center antenna reflected from an unknown object and received by the antenna mounted on the right finger. As with the initial system, these spectral values are obtained by subtracting an object absent baseline spectrum from the total measured spectrum. The reflected spectral components are sequentially phase unwrapped and sequentially input to the first ANN layer. A unique set of phase unwrapping vectors are calculated for each contour within the object field. The exact number of independent contours is based on size of the field and the illumination frequencies.

Each object is represented by a set of output neurons which have previously been trained to identify the object and the location contour. Output neurons are observed as the first set of input vectors are sequentially unwrapped and input to the first ANN processor. The correct output neuron should go high when the input

vectors are incremented to the delay associated with the contour containing the object.

The second ANN processor is served with its set measurement vectors and the outputs observed as the measurement vectors are unwrapped and input. Again, an output neuron should go high at the delay corresponding to the contour that intersects the object. The intersection of the two elliptical contours having high output states identifies the location of the object. One contour is calculated by the first ANN processor, the second contour is calculated by the second ANN processor.

Back-propagation training is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a multilayer feed-forward perceptron and the desired output. This technique requires a differentiable function that is non-linear, which for the Intel i80170 chip is the conventional sigmoid function. The training of either of the processors, for a field containing a single object will be described. This training starts by initializing the ANN processor weights to small random values. The next step is to calculate the output of this processor using the spectrum values measured at the start of a contour and unwrapped for it's delay. The weights are adjusted to minimize the error, (output – desired output)^2 by a recursive algorithm that adjusts the weights by starting at the output nodes and working back through the hidden layer. This process is iterated through many cycles as spectrums recorded along all elliptical contours are sequentially input. The process is stopped when the residual is within predetermined acceptable limits. Figure 6 is a simplified sketch of the desired output function. The output neuron designed to identify the contour C(L) should be high for any of the unwrapped input spectrums recorded when the object was located on or near this particular contour. Connections shown in Figure 6 are limited to those connected to the first perceptron of the hidden layer.

C(I) = ELLIPTICAL CONTOUR (I)
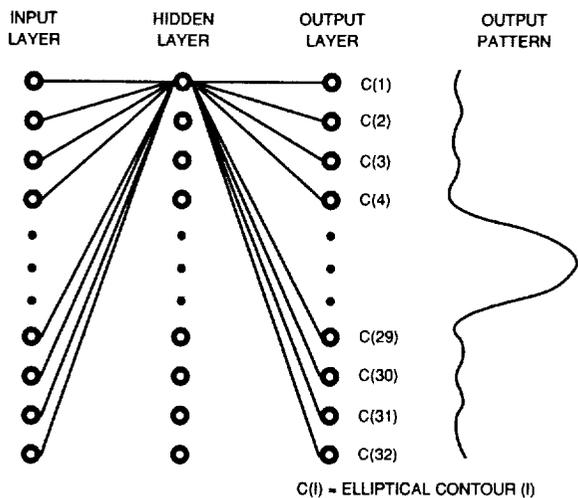
Figure 6. ANN Training Pattern

A modification to a probability based DF emitter location algorithm, is used to estimate the location of and object. Histories of all previous estimations provide increasingly accurate joint probability location estimations as additional measurements are performed.

A high neuron output representing a particular elliptical contour indicates that there is a high degree of probability that the object is on or near this contour. This probability is represented by a surface density that has unity height along the contour and has the conventional gaussian shaped pattern in directions normal to this surface.

Conventional radar range equations predict measurement accuracies that are inversely proportional to range to the fourth power. This range effect is included in our object location estimations by using standard deviations given by:

$$\sigma\,(\,r\,) \;=\; \sigma_{\text{min range}}\,[\,\frac{\text{range}}{\text{min range}}\,]^4$$

EQ-4

This increase in sigma at longer ranges produces a probability surface that has a rapidly

rising ridge in the direction normal to the contour containing the object when these contours are approached from the side nearest the robotic hand.

Conceptual probability surface densities generated for a cube located in front of robotic hand mounted array is shown below in Figures 7(a), 7(b) and 7(c). Figure 7(a) shows an unnormalized theoretical probability density surface based on the elliptical contours associated with the center-right antenna pair. This depiction demonstrates the start of the process used to locate an object, such as the cube shown in Figure 7(a). Figure 7(b) shows the surface associated with the center-left antenna pair. Figure 7(c) is joint probability density surface generated by the product of the surfaces shown in (a) and (b).

A short series of tests were conducted to verify the ANN-MV concept. The proof of concept was based on the second training and processing method. These tests used the experimental system shown in the schematic, Figure 4, to record process and move a robotic hand toward a simple object. The final goal of these experiments was to accurately move the robotic hand into a position that would permit the grasping of a small object. The robotic fingers on the simple hand was not moveable so this next step in the general solution to robotic problems could not be demonstrated.

Several key indicators, each pointing to successful experiments, were observed as the experimental process proceeded. The first of these was the ease of Intel i80170 ETANN chip training. The i80170 chip can be trained in two distinct ways. The slow direct way is to train with the chip-in-the-loop. We used a second faster way that records a typical on chip sigmoid function, then places this function into an external program that emulates the chip and trains with a procedure identified as off-line learning.
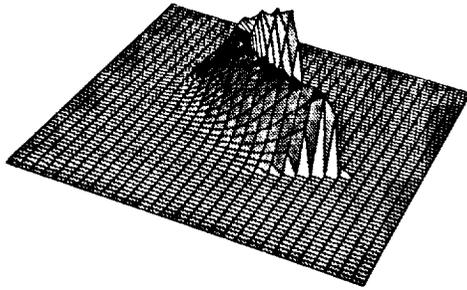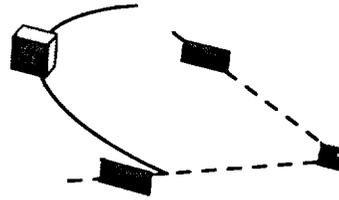
Probability density surface   **Right elliptical equal time delay contour**

Figure 7(a). Surface and Contour Based on Center to Right Antenna Measurements
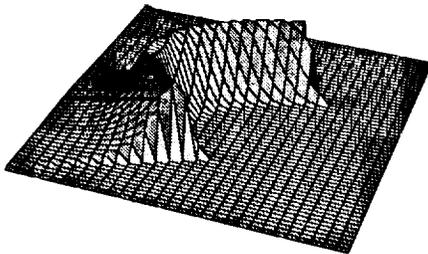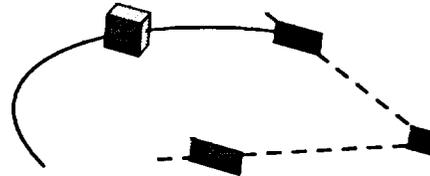
Probability density surface   **Left elliptical equal time delay contour**

Figure 7(b). Surface and Contour Based on Center to Left Antenna Measurements
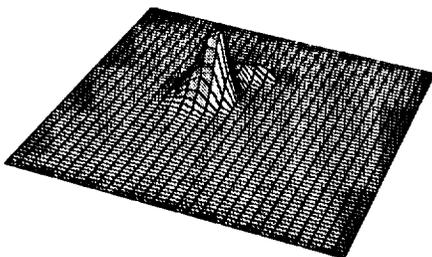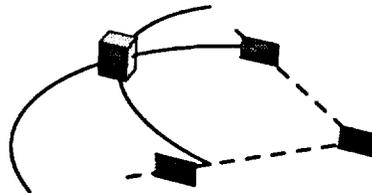
Joint probability density surface   **Left/Right elliptical equal time delay contours**

Figure 7(c). Surface and Contours Based on Previous Two Sets of Measurements

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An alternate is to learn off-line, then download these neuron weights, and then follow with the more accurate chip-in-the-loop learning. The off-line learning process produced accurate guidance commands when used in conjunction with our second unwrapped vector input technique. Chip-in-the-loop training was not required. A strong indicator of robust robotic operation was the ability of the hand to follow a can that was moved between processing steps.

A HP 8510 network analyzer was used to measure the reflected signals at sixteen uniformly spaced frequencies between 2 GHz and 6 GHz. Probability density surfaces were computed by the Vectra PC using outputs generated by the two ANN chips. The maximum of the product of these surfaces identifies the location of the object, which for this set of experiments was the coordinates of an aluminum soda can. Figure 8 shows the product probability estimate based on calculations generated as the robotic hand progressed from its (0., 0.) starting location. The final pair of contours were based on artificial neural network output processed microwave spectrums recorded at a hand location of 7.3 cm, 18.1 cm). The sharp peak at (8 cm, 28 cm) is within approximately 2 cm of the correct location. When the robotic hand moves to this location, it is in very close to the desired location. Subsequent moves of an articulated hand could accurately close on this cylindrical object.

CONCLUSIONS

The techniques describe herein provide the first stage in the solution to many robotic vision problems. The next stage, that of providing objects coordinates and subsequent movements for grasping, a difficult problem for optical vision systems, should be a fairly simple problem for Microwave Vision-Artificial Neural Network processing. Here, the robots fingers are in the electrical near field of the object where increasingly accurate microwave measurements can be performed. The Range[4] problem no longer applies. At this point the elliptical contour technique will be discarded and it is anticipated that full cross spectrum ANN training commands will be applied. In the simplest sense, as the antennas on the robotic fingers approach the object, their radiation will be blocked, generating a clear signal that the fingers are ready to touch the object. Obviously the MV-ANN system will not look for this condition, instead the ANN processor will have been trained to output a signal that indicates that the hand has "CLOSED ON THE OBJECT".

REFERENCES

[1] K.A. Struckman, "Microwave Vision for Robots", Patent Disclosure D-4030, Sept. 18, 1985.

[2] K.A. Struckman and R. Martel, "Microwave Vision for Robots Using Artificial Neural Network Processing", Dec. 22, 1992.

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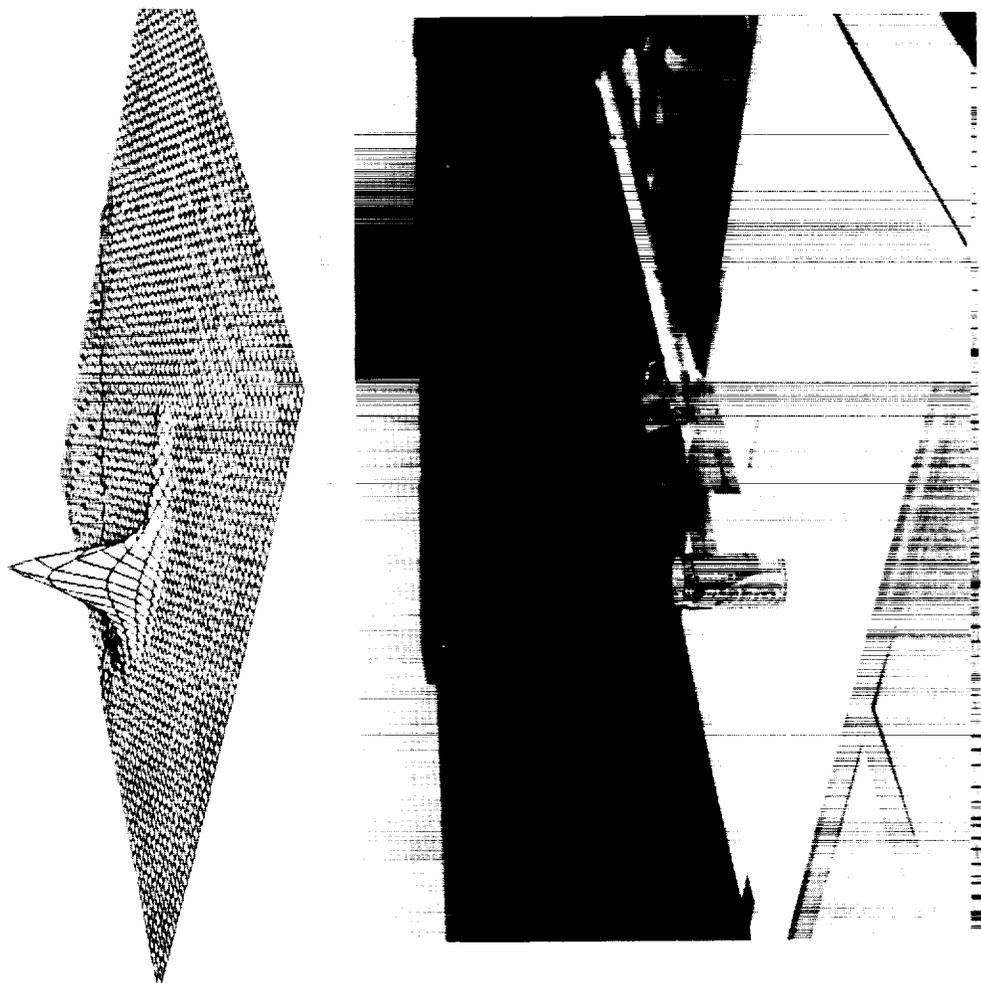
Figure 8. This is the Final ANN-MV probability Density Surface Calculated for this Experiment. Here the Object, a Soda Can is Still at (10 cm, 28 cm), but the Hand has Moved Forward to Coordinates (7.3 cm, 18.1 cm). This Last Joint Probability Surface Maximum has a well Defined Peak at (8 cm, 28 cm).