# Intelligent Alignment of Waveguide Filters Using a Machine Learning Approach

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*Abstract* —This paper investigates the use of a machine learning system applied to the tuning of waveguide filters. This system employs techniques from pattern recognition and adaptive signal processing. The manual tuning of the waveguide filters is very time consuming and expensive and a skilled operator is required. Here, the machine learning system is adapted in such a way that it can assist an unskilled operator to perform fast and accurate tuning of these filters.

## I. Introduction

WAVEGUIDE filters (WGF's) are tuned once the filters have been assembled. The traditional approach to the tuning of these filters is to check the response of the filter at a number of critical frequencies and adjust a set of tuning screws in order to bring the filter response within some predefined specification. This procedure is carried out manually and can be thought of as a humanly performed real-time optimization. This tuning method is very time consuming and expensive and a skilled operator is required. Therefore, automatic tuning of these filters would be a more desirable and cost-effective alternative. In spite of the wide range of applications for waveguide filters, there have not been many contributions to the studies of computer-aided alignment of WGF's. In previous publications, standard procedures for manual tuning of these filters have been described [1]–[3], but these methods are not suitable for constructing a computer-based tuning system. Work on computer-aided filter alignment has been very limited [4], and these methods are predominantly based on theoretical treatment and modeling of the filters.

In this paper a different approach is introduced for the tuning of the waveguide filters. Here a machine learning system (MLS) is adapted in such a way that it can assist an unskilled operator to perform accurate and fast tuning of the filters. The machine learning approach is based on the manipulation of some raw data to extract a set of salient features which have strong significance in the behavior of the filters. These features are derived visually, by comparing the characteristics of a tuned filter with a faulty filter with known levels of maladjustments.

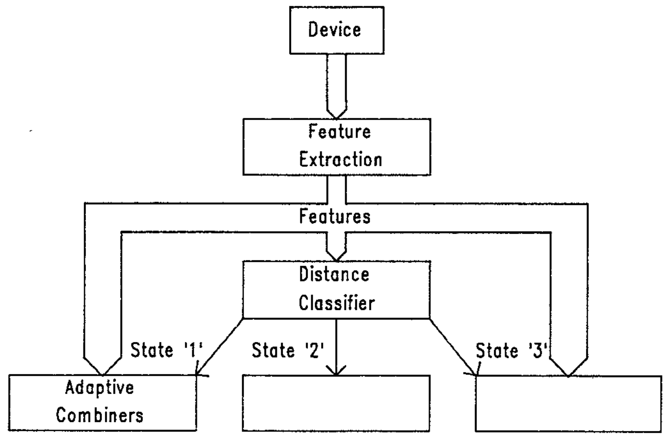


Fig. 1. Block representation of the machine learning system.

In Section II, we briefly describe the main principles of the MLS used. Section III gives an introduction to waveguide filters and illustrates how they are tuned manually. In Section IV, we consider the adaptation of the MLS to this problem. The MLS has been used for fine tuning of WGF's and Section V presents some results. The MLS approach is not yet a complete solution to this problem, and some manufacturing tolerances have been ignored, but this paper presents a new approach for the development of an automated tuning system for WGF's.

## II. Outline of the Machine Learning System

Fig. 1 shows a block representation of the MLS used. The overall system can be thought of as an equivalent to an expert system, where there is a "training mode" and a "use mode." In the training mode, the expertise of a skilled operator is represented and stored in such a way that it can be accessed later in the use mode. The main difference between the MLS and a conventional expert system is in the way in which the information is obtained and represented. In a conventional expert system, the information is stored in the form of explicitly stated rules, and in the use mode the system makes decisions by matching the inputs to the predefined rules. In the MLS approach, we employ techniques from pattern recognition and adaptive signal processing to form two types of classi-

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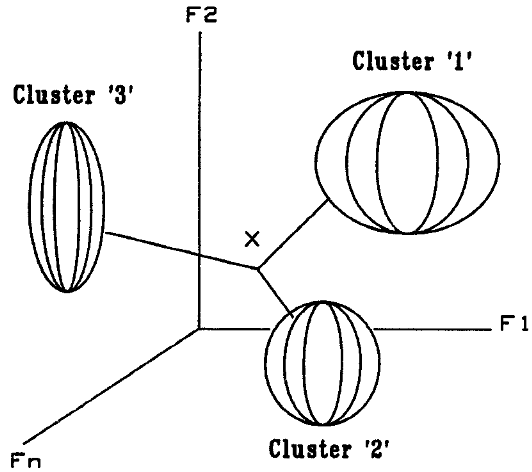



Fig. 2. Distance classifiers.

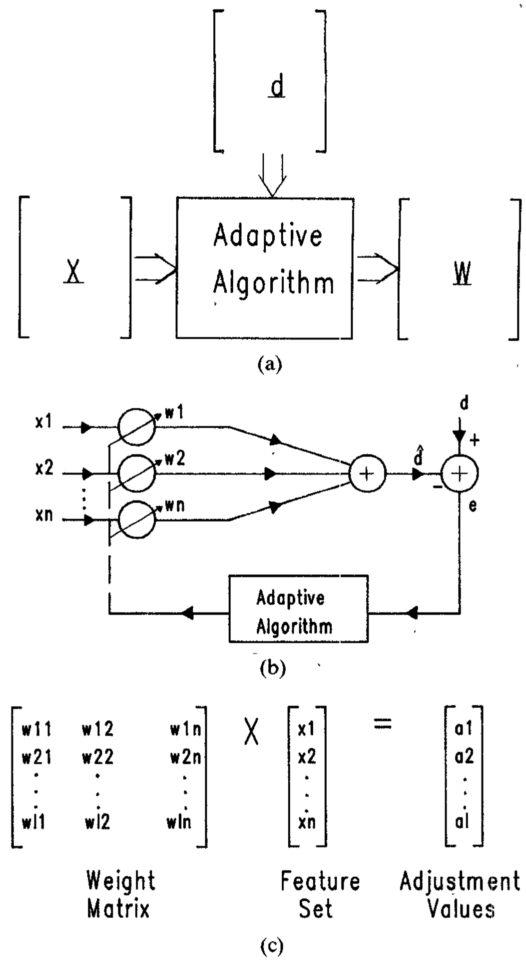



Fig. 3. Adaptive combiners. (a) Training mode. (b) Linear combiner. (c) Use mode.

fiers, distance classifiers and adaptive combiners. In the training mode, the "expert" information is represented in the form of mathematical relationships in the classifiers.

In general, the distance classifiers are used to narrow down the problem area, and the adaptive combiners are used for finer adjustments. When the MLS is used for any application, the first step is to decide on a reference characteristic for the device under test (DUT) which would represent the specifications required from the device. This reference characteristic must be unique for every set of adjustments, since an optimal setting cannot be achieved. The next step is to decide on a number of salient features within the reference characteristic that reflect the properties and the sensitivity of the adjustable parameters defined for the device. These two steps are of primary importance in the adaptation of the MLS to a particular problem, since the rest of the system depends on these decisions. In the following sections, we describe the training and the use mode of the distance classifiers and the adaptive combiners.

### *A. Distance Classifiers*

As mentioned above, the distance classifiers are used to distinguish between different states which may exist for the device. In the training mode, an $n$-dimensional feature space is formed (Fig. 2) where $n$ is the number of features. Next, a number of feature sets are collected for each state of the device, and each feature set is represented as a point in the feature space. By collecting a number of points belonging to a particular state, we form a cluster. In the use mode, a new feature set is generated from the DUT, and this would again be represented as a point in the feature space, i.e., point $\underline{x}$ in Fig. 2. In order to decide which cluster this new point lies within, we find the distance between $\underline{x}$ and each of the clusters, i.e., $r_1$, $r_2$, and $r_3$. The simplest form of classification consists in measuring the geometric distance of the new point, $\underline{x}$, from the centroids of each cluster. The main disadvantage of this method is that it does not take into account the distribution of the points in the clusters. A more general measure of the distance, known as the Mahalanobis distance [5] (see Appendix I), can be used which requires not only the centroids of each cluster but also the variances and the covariances of the points within the clusters.

### *B. Adaptive Combiners*

The adaptive combiners in the MLS are implemented using $l$ linear combiners in parallel, where $l$ is the number of adjustable parameters in the device. Fig. 3(a) shows a block representation of the adaptive combiners in the training mode, and Fig. 3(b) illustrates the structure of one combiner trained for one particular fault. During the training mode, feature sets are collected from the DUT when its performance meets the specification, i.e., it is close to a good device, and also when the parameters of the device are maladjusted to some known values. These feature sets are represented as matrix $\underline{x}$ in Fig. 3(a). Corresponding to $\underline{x}$, matrix $\underline{d}$ is generated which contains the values of each of the adjustable parameters of the DUT corresponding to the measured features. For example, when the device is behaving correctly, the corresponding desired values for all the parameters would be zero. Using these two matrices as the inputs to a recursive least squares algorithm (RLS) [6], [7], see Appendix II, we estimate the weight matrix $\underline{w}$ for

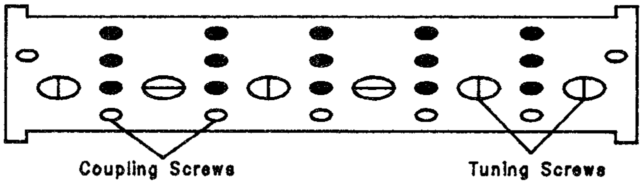



Fig. 4. Top view of a six-cavity waveguide filter.

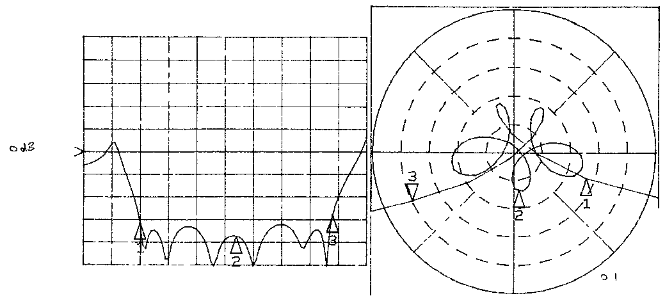


Fig. 5. The $S_{11}$ polar and log magnitude characteristics of a good filter. For log magnitude, the vertical scale is 10 dB per division and the horizontal scale is 20 MHz per division. The center line corresponds to 0 dB return loss. For polar plot, return loss is displayed radially from the center on a linear scale with a magnitude of 0.1 ($-20$ dB), corresponding to the outer ring. Phase information is measured as angular rotation from the right-hand horizontal axis. Markers display complex response near to the band edges and the center frequency. Filter center frequency $=10.532$ GHz, bandwidth $=0.138$ GHz, and minimum loss $=32.1$ dB.

the linear combiners. After training, the linear combiners are supplied with the estimated weight values to provide a parallel measurement system, Fig. 3(c), which indicates the magnitude and the direction of the required adjustments in order to bring the performance of a faulty device within required specifications. Matrices $\underline{x}$ and $\underline{d}$ have dimensions $n$ by $m$ and $l$ by $m$, respectively, where $m$ is the number of training feature sets. The weight matrix $\underline{w}$ will have a dimension $n$ by $l$.

In order to summarize the principle of the MLS, the following steps must be taken when adapting the MLS to any application. These steps should not necessarily be taken in the order given here.

1) Decide on the reference characteristics of the DUT and the corresponding data collection technique.
2) Decide on a set of salient features to extract from the reference characteristics.
3) Decide how the distance classifiers and the adaptive combiners will be used.

The MLS described here allows "learning" at any time in the use mode. In other words, if in the use mode the MLS fails to indicate the correct adjustments, then, once the faults have been found by some other means, the corresponding feature set may be entered in the system as a further training example. In this way, the MLS will improve its performance with experience.

## III. Waveguide Filters (WGF's)

The MLS has already been used for fault diagnosis in communications equipment [8], [9], and the waveguide filter example has been used as another application for the MLS. There are two main reasons for this choice. One is the fact that WGF's are very sensitive to small maladjustments of their tuning screws and there is a high level of interaction between the screws. Therefore, it is a very challenging problem for the MLS. The other is the fact that these filters take a very long time to be tuned manually. As a typical example, a sixth-order filter, which has 13 screws, six for tuning and seven for coupling, would take approximately 35–45 minutes to be tuned by a skilled operator. Therefore, there is a demand for a computer-based filter tuning system with the objective of reducing the time taken to tune the devices.

Fig. 4 shows the top view of a six-cavity WGF. There are two types of screw. One type is the tuning screw, bigger in size; the other is the coupling screw. The tuning screws are used to move the resonant frequencies of the corresponding cavities. The coupling screws between the two cavities are used to couple the adjacent cavities, and the two end coupling screws are used to couple the filter to the outside world.

The filters used for this study were supplied by Ferranti (Dundee, Scotland). In the production environment, the operator tunes the filters manually by looking at the log magnitude of the return loss of the filter, i.e., $S_{11}$. Fig. 5 shows a typical $S_{11}$ characteristic which meets a certain set of customer specifications. The procedure adapted at Ferranti for the manual tuning of these filters can be summerized as follows:

1) All the screws are removed.
2) The tuning screws are inserted one at a time, starting from the input to the filter. Each time a screw is inserted, it is turned clockwise to bring the resonant frequency of the corresponding cavity within the filter bandwidth.
3) When all the turning screws are inserted, there must be $n$ resonant frequencies in the passband, where $n$ is equal to the number of cavities in the filter. Thus each tuning screw corresponds to a notch in Fig. 5. However, the return loss characteristic of the filter does not always show all the resonant frequencies clearly. At this stage, the tuning screws are adjusted to minimize the return loss response of the filter as far as possible before the coupling screws are inserted.
4) Finally, the coupling screws are inserted. At this stage the operator needs to adjust all 13 of the screws in such a way that the $S_{11}$ of the filter meets all the customer specifications.

In this process, steps 1 and 2 can be done very quickly and easily by the operator. Most of the tuning time is taken by steps 3 and 4. Therefore, the intent now is to adapt the MLS to take over the tuning operation from step 3 onwards.

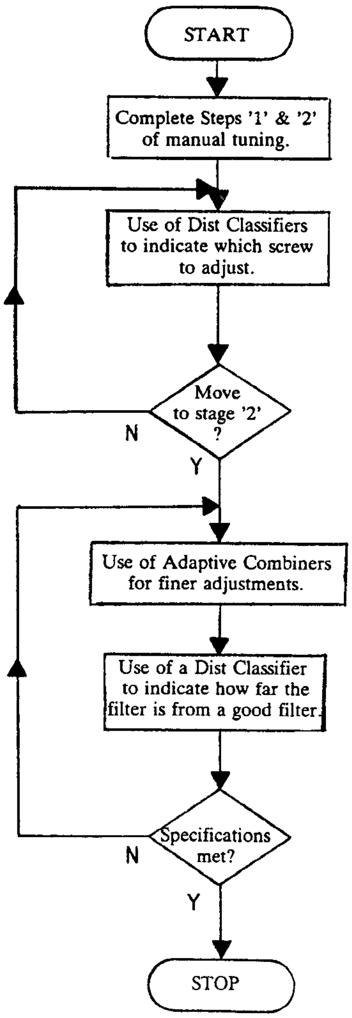



Fig. 6. Flow chart of the machine learning system operation for waveguide filter tuning process.

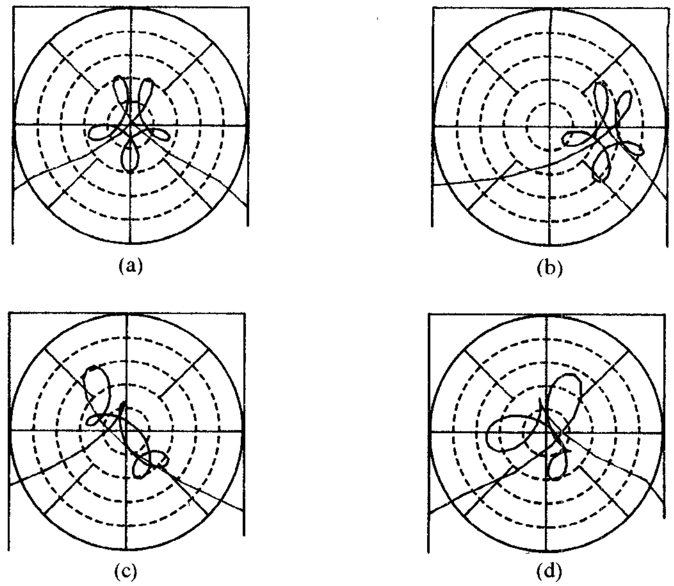



Fig. 7. Effects of screw maladjustments on the polar plot. (a) Reference filter. (b) 1 clockwise. (c) 3 clockwise. (d) 5 clockwise.

## IV. Adaptation of the MLS for Tuning WGF's

As mentioned at the beginning of Section II, the most important steps when adapting the MLS to a problem are to decide on a reference characteristic for the device and a set of salient features.

When WGF's are tuned manually, the log magnitude of $S_{11}$ is taken as a reference and the specifications of the filter are based on this characteristic. However, the log magnitude of $S_{11}$ is not unique. In other words, a filter whose log magnitude meets all the specifications may still have very poor group delay and phase characteristics. Thus, the polar plot of $S_{11}$ has been taken as the reference characteristic for the WGF's, since it contains both the log magnitude and the phase information (Fig. 5).

Having decided on the reference characteristic, the next step is to decide on a set of features which reflects the properties and the sensitivity of the screws on the polar plot. The features which are used in the distance classifiers are not necessarily the same as the features for the adaptive combiners. Therefore, let us first decide how we intend to adapt the MLS to this particular problem.

As mentioned in Section III, the first two steps of the manual tuning of WGF's can be done quickly and easily by the operator. The first stage of the MLS tuning process would be to bring the response of the filter as close as possible to a good response. In terms of the polar plot, this means that for a six-cavity filter we can see the five loops in the polar plot. This can be achieved by the use of the distance classifiers which would give indications of which screw brings the response of the filter closer to the specifications. The next stage would be to use the adaptive combiners for a finer adjustment of the screws. A separate distance classifier can also be used to indicate how far the response of the filter deviates from a good filter. This classifier is trained on filters which meet all the required specifications. Therefore it only has one cluster in the feature space. The distance from the untuned filter to this cluster would indicate how far away the filter is from the specifications. The cluster also contains filters with different tolerances in their specifications. Using this classifier, the operator can decide when to stop the tuning process.

Fig. 6 shows a flow chart of the complete MLS approach for the tuning of WGF's. In the next section we consider the use of the adaptive combiners for the last stage of the tuning process.

### *A. Use of Adaptive Combiners*

Initially, we assume that the filter coupling screws are correctly adjusted and are left untouched. Therefore the tuning screws will be taken as the adjustable parameters for the filter. It was decided above that the polar plot of $S_{11}$ would be taken as the reference characteristic. Now we need to decide on a set of salient features which will be used in the system. Let us now assume that the polar plot of the filter in Fig. 7(a) meets all the specifications. In order to decide on a feature set, it is necessary to investigate the effects on this polar plot when the tuning screws

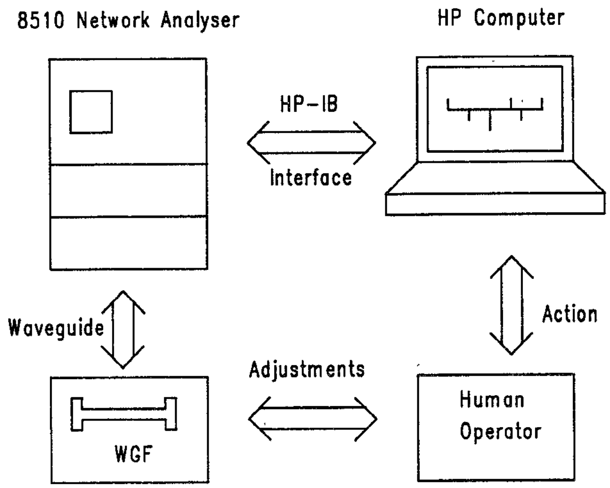



Fig. 8. Schematic diagram showing the instrumentation configuration used in the waveguide filter tuning application.

are maladjusted from their correct positions. Fig. 7(b)–(d) shows the polar plots of $S_{11}$ for maladjustment of selected tuning screws. The rest of the screws have very similar effects. From these polar plots we can conclude the following points:

- Fig. 7(b) illustrates translation of the polar plot, i.e., the geometric mean of the polar plot has moved.
- Fig. 7(c) illustrates deformation and compression of the polar plot, i.e., the circular shape of the polar plot has been deformed into an elliptical shape.
- Fig. 7(d) illustrates the expansion and the contraction of the loops in the polar plot.

The salient features which are selected to describe these geometric changes are as follows,

- Position of the mean of the polar plot, 2 features.
- Position of the beginning and the end of the polar plot, 4 features.
- Center frequency of the filter, 1 feature.
- Area of the loops, $(n-1)$ features.
- Distance between the center of the loops, $(n-1)$ features.

Here $n$ is the order of the filter, i.e., the number of cavities. These features are calculated using the real and imaginary parts of $S_{11}$. The feature extraction using the real and imaginary parts of the polar plot is described in detail in the next section.

### B. Feature Extraction

Fig. 8 illustrates how the filters have been connected to a commercial network analyzer (Hewlett Packard 8510). The analyzer communicates with an HP300 series computer through an HP-IB interface cable. The network analyzer provides the real and imaginary parts of the polar plot, i.e., $x$ and $y$ coordinates, in a discrete form. These points are manipulated in order to generate the features listed in the previous section.

The computer spans the passband of the filter and collects between 60 and 101 points. The mean of the polar plot can be calculated by averaging the $x-y$ coordinates of the polar plot. The beginning and the end of the polar plot correspond to the first and the second edge frequencies of the filter. The areas of the loops are calculated by first estimating the points of intersections in the polar plot and then by performing numerical integration over the loops. After obtaining the points of intersection, the centers of the loops can be found by averaging the $x-y$ coordinates for each loop. The distance between the centers of the loops can then be found using the coordinates of the loop centers.

The data collection and feature extraction part of the MLS takes about 35 seconds to complete. The time taken by the adaptive combiners to come up with a set of adjustments is negligible compared to the above time. Thus, a new adjustment can be made by the operator in under one minute.

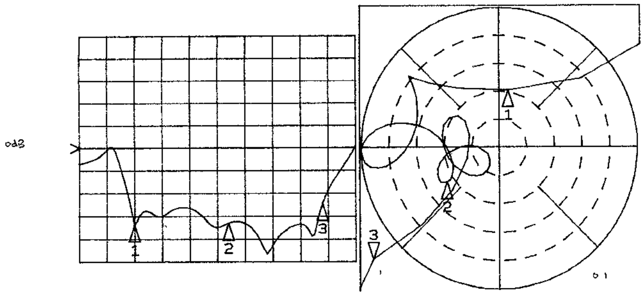
In the next section, we illustrate how the adaptive combiners have been used for fine tuning of a filter.

## V. Results

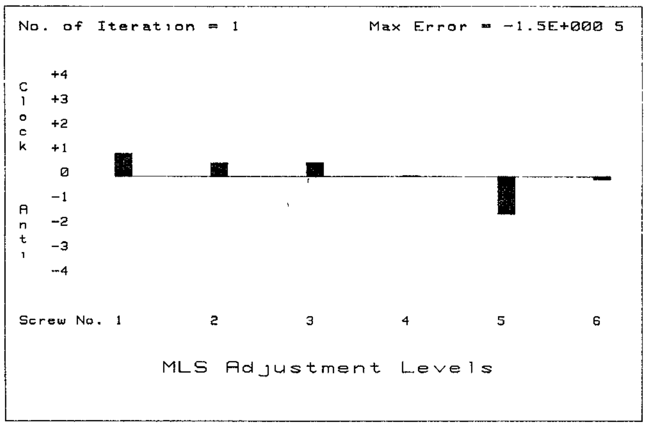
The output of the MLS consists of a graphical display of the adjustment levels for each of the screws, which provides the magnitude and the direction of the adjustments, the number of iterations, the maximum error, and the screw which has generated the maximum error. Fig. 5 shows the magnitude response and the polar plot of a filter which has been taken as the reference filter in the training mode, i.e., a good filter. Fig. 9(a) shows the $S_{11}$ of an untuned filter, and Fig. 9(b) shows the output of the MLS for this filter state. The maximum error is due to screw number 5, and it is equal to $-1.5$ units. Fig. 10(a) shows the output of the MLS after four iterations, and Fig. 10(b) shows the filter response at this stage. It can be seen that the adjustment levels for all the screws are very close to 0 and the maximum error is due to screw number 5 and is equal to 0.23. At this stage the response of the filter is within the specifications set by the reference filter.

## VI. Conclusion

The MLS described in this paper can be thought of as an expert-system shell. The overall structure of the system (Fig. 1) is unchanged when adapting the system for a wide variety of problems. The implementation of the MLS is in Pascal and is organized in such a way that, in the training mode, the user provides the system with a file which contains the training feature sets and the desired output values. In the case of the distance classifiers, the desired values would be the name of the clusters in the feature space; for the adaptive combiners, they would be the required adjustment levels. The program will then generate the mean and covariance matrices for each cluster in the distance classifiers, and the weight matrix for the adaptive combiners. The numbers of features, clusters, parameters, and training examples are set by the user at the beginning of the program. In the use mode, the program requires a feature set from the DUT, calculates how far the new

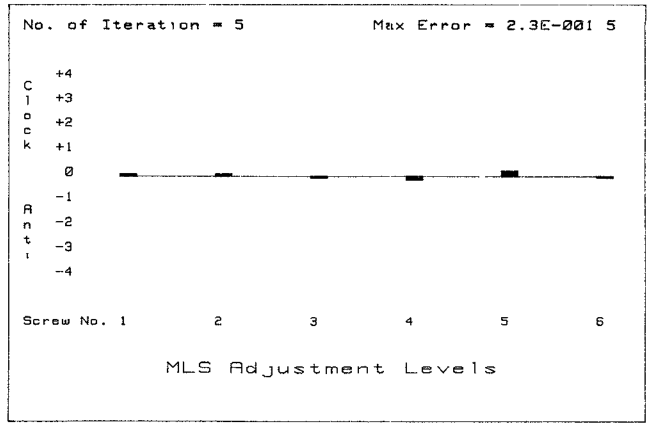


(a)

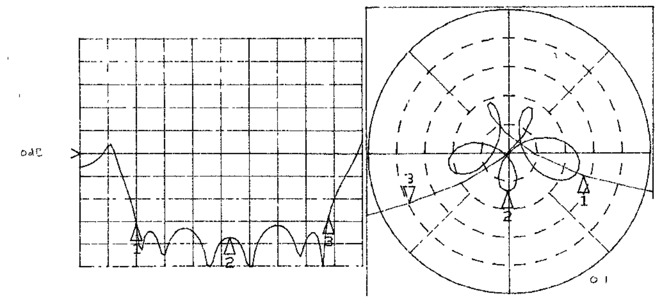



(b)

Fig. 9. (a) The $S_{11}$ characteristics of an untuned filter (scale as in Fig. 5). Center frequency = 10.531 GHz, bandwidth = 0.136 GHz, and minimum loss = −26 dB. (b) The MLS output for filter in (a).




(a)



(b)

Fig. 10. (a) The MLS output after four adjustments. (b) The $S_{11}$ characteristics corresponding to the tuned filter. Center frequency = 10.532 GHz, bandwidth = 0.138 GHz, and minimum loss = −32 dB.

feature set deviates from the predefined clusters in the feature space, and estimates the magnitude and the direction of the adjustment required for each of the parameters. Therefore the user needs only to interface the MLS package with its application program, which generates the desired feature sets for the particular problem.

The high level of interaction between the screws on the WGF and the sensitivity of the filter, provided a particularly difficult problem for the MLS. However, the results presented in this paper show that the tuning of WGF's can be achieved by dividing the tuning process into two stages. Here we only considered the use of the adaptive combiners for fine tuning of the filter and also reduced the number of adjustable parameters to the tuning screws, assuming that the coupling screws are correctly adjusted and are left untouched. Work is in progress to investigate the effects of the coupling screws and how to adapt the MLS for the first stage of the tuning process, i.e., use of distance classifiers for rough tuning of the filter.

## Appendix I
## The Mahalanobis Distance Classifier

The Mahalanobis distance classifier is one of the similarity measures used in the field of pattern recognition [3]. The main advantage of using the Mahalanobis distance is when the points in the clusters are not normally distributed, i.e., there exist correlations between the features. The correlation between the features is expressed by the covariance matrix. The Mahalanobis distance, $r_i^2$, between the point $\underline{x}$ to the $i$th cluster is given by

$$r_i^2 = (\underline{x} - \underline{m}_i)^T C_i^{-1} (\underline{x} - \underline{m}_i) \tag{A1}$$

where $\underline{m}_i$ and $C_i$ are the mean and the covariance matrices of the $i$th cluster, respectively, and are given by

$$\underline{m}_i = \frac{1}{N} \sum_{i=0}^{N} \underline{x}_i \tag{A2}$$

$$C_i = \frac{1}{N} \sum_{i=0}^{N} \underline{x}_i \cdot \underline{x}_i^T - \underline{m}_i \cdot \underline{m}_i^T. \tag{A3}$$

Here $N$ is the number of points in the cluster and $T$ denotes the matrix transpose operation. The form of the covariance matrix corresponds to an ellipsoidal cluster where the correlation between the features is expressed by the nonzero terms in the nondiagonal elements of the matrix.

## Appendix II
## The Adaptive Combiners

The adaptive combiners employ techniques from the field of adaptive signal processing [4]. There are $p$ combiners for $p$ outcomes, i.e., one combiner for each outcome. The input features to all the combiners are the same but each combiner is trained on different desired values.

Fig. 11 illustrates the $i$th combiner where $\underline{x}^T(k)$ is the present feature set, $\underline{w}(k)$ is the weight vector, and $\hat{y}(k)$ is

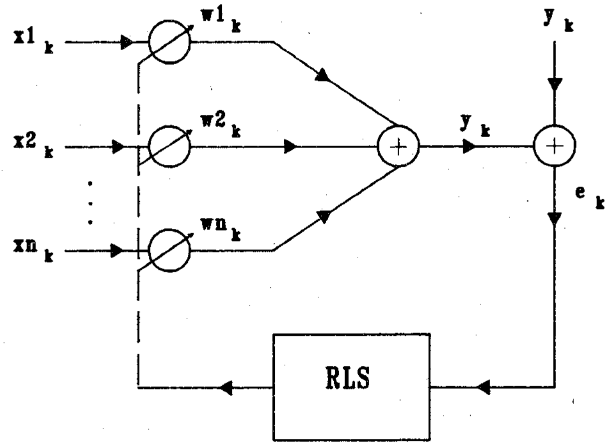


Fig. 11.

the estimated combiner output. From Fig. 11 the estimated output is

$$\hat{y}(k) = \underline{x}^T(k)\underline{w}(k). \tag{A4}$$

The error in the training mode can be expressed in terms of the desired value, $y(k)$, and the estimated output as follows:

$$e(k) = y(k) - \hat{y}(k). \tag{A5}$$

The RLS adaptive algorithm is used to adjust the weights in order to minimize the mean squared error. It has been shown [4] that the optimal weight, $\underline{W}_{\text{opt}}$, is given by the Wiener [6] solution,

$$\underline{W}_{\text{opt}} = \Phi_{xx}^{-1}\Phi_{xy} \tag{A6}$$

where $\Phi_{xx}$ is the autocorrelation function of of $\underline{x}$, and $\Phi_{xy}$ is the cross-correlation function of $\underline{x}$ and $y$. In the RLS algorithm [4], [5], the present weights, $\underline{w}(k)$, may be expressed in terms of the previous weights by

$$\underline{w}(k) = \underline{w}(k-1) + R_{xx}^{-1}(k)\underline{x}(k)e(k) \tag{A7}$$

where $R_{xx}$ is an estimate of $\Phi_{xx}$ given by

$$R_{xx} = \sum_{n=0}^{k} \underline{x}(n)\underline{x}^T(n). \tag{A8}$$

$R_{xx}^{-1}(k)$ can be expressed in terms of a standard matrix identity by

$$R_{xx}^{-1}(k) = R_{xx}^{-1}(k-1) - \frac{R_{xx}^{-1}(k-1)\underline{x}(k)\underline{x}^T(k)R_{xx}^{-1}(k-1)}{1+\underline{x}^T(k)R_{xx}^{-1}(k-1)\underline{x}(k)}. \tag{A9}$$

The RLS algorithm guarantees convergence within $2N$ input samples, where $N$ is the number of weights, and the convergence is not affected by the input signal coloration. This form of RLS has an infinite memory. In other words, the weights are functions of all the sample inputs. It is useful to introduce a forgetting factor into the algorithm in order to give greater importance to the recent training samples than to the old ones. In this way the combiners are open to further training as the requirements are changed. One way of accomplishing this would be to apply a time-varying exponential window to the recursions. In this case the recursion given for $R_{xx}^{-1}(k)$ in (A9) is modified to

$$R_{xx}^{-1}(k) = \frac{1}{\lambda}\left(R_{xx}^{-1}(k-1) - \frac{R_{xx}^{-1}(k-1)\underline{x}(k)\underline{x}^T(k)R_{xx}^{-1}(k-1)}{\lambda+\underline{x}^T(k)R_{xx}^{-1}(k-1)\underline{x}(k)}\right) \tag{A10}$$

where $0 < \lambda < 1$ but usually it is kept in the range $0.9 < \lambda < 1$.

## Acknowledgment

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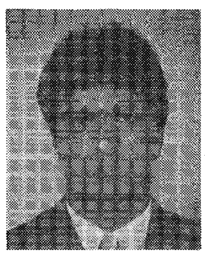

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