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An Intelligent Ultrasonic Flow Meter for Improved Flow Measurement and Flow Calibration Facility

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Abstract* – An increasing need for reduced uncertainty has forced metrologists to look for novel ways to improve the calibration standards for flow. The NIST Fluid Flow Group is experimenting with the use of an advanced ultrasonic flow meter (AUFM) to improve flow measurement and to detect the dynamic properties of calibration facilities. Ultrasonic technology is evolving rapidly and technical advances have significantly improved flow measurement in continuous industrial processes. The AUFM couples multi-path ultrasonic sensing capabilities with pattern recognition software to predict likely flow fields and their probability of existence. The knowledge encoded in the AUFM is derived from training exercises that use computational fluid dynamics and experimental results to teach a flow field recognizer (FFR) via a learning algorithm. A four-path ultrasonic flowmeter prototype has been used to demonstrate the AUFM operational principle. Results showed that the four-path meter can successfully identify flow patterns among several selected flow fields. The results also indicated that the ability of the FFR to identify flow patterns increases as the accuracy of the sensor increases, while it decreases as the number of flow patterns considered increases. In addition to being used as a flow diagnostic tool, the AUFM could prove beneficial in field applications where installation effects can lead to gross errors when ultrasonic signals are evaluated using conventional integration techniques.

Keywords* – Ultrasonic Flowmeter, Artificial Intelligence, Flow Measurement.

I. INTRODUCTION

The National Institute of Standards and Technology (NIST) has been searching for novel ways to reduce the uncertainty and improve the operation capability of its flow calibration facilities [1]. The operation of a good flow calibration facility requires not only an accurate determination of the average flow rate, but should also be able to maintain and characterize important flow field properties, such as the flow steadiness and real time flow profiles.

Accurate flow measurement is a challenging task, especially in industrial applications. In the last decade, ultrasonic techniques have significantly improved flow measurement and its use for measurements in continuous industrial processes has been gaining acceptance [2]. The ultrasonic technique for measuring flow offers many potential advantages over traditional measurements. The instrumentation can be robust, and non-invasive. However, as with most flow meters, the accuracy of the flow rate determination in non-ideal pipe configurations depends on the meter design and sensing technology. Typically, ultrasonic flow meter manufacturers assumed axisymmetric 1-D ideal velocity profiles to design their transducer arrangements. However, these assumed profiles seldom occur in real applications, leading to significant errors [3, 4].

Metrologists have relied on the assumption that the flow fields produced by their calibration facilities are ideal pipe flows. An "ideal installation" is one where the pipe flow displays an equilibrated velocity distribution similar to that naturally produced by long straight lengths of constant diameter pipe. Such fully-developed velocity profiles (*i.e.,* the profile is streamwise invariant) can be closely approximated by devices known as flow conditioners which help reduce the length of straight pipe required for an ideal installation. Typical "non-ideal" pipe flows can be found downstream from elbows or reducers. Research has shown that deviations from the ideal assumption can lead to significant errors in the meter calibration, even when the calibration system may provide a good average flow rate determination. Although various techniques exist for evaluating the flow profile in a calibration facility, their high cost only allows for their sporadic use, thus providing data that represents the conditions at the time of the evaluation, not at the time of the meter test.

The objective of this study is to improve the accuracy and extend the capability of ultrasonic flow meters. This work focuses on flow measurement performance prospects using a special neural network approach. The project is intended to provide a comprehensive understanding of the operational principle of pattern recognition as applied to flow field detection and to serve as a foundation to advance the development of intelligent ultrasonic flow meters. Although the purpose of this research is to diagnose the flow field and to reduce the uncertainty of flow calibration facilities, the use of an advanced ultrasonic flow meter (AUFM) could prove beneficial in field applications where installation effects can lead to gross errors when ultrasonic signals are evaluated using conventional integration techniques.

II. PRELIMINARIES

A. Basic Ultrasonic Flow meter

A detailed description of ultrasonic metering can be found in [5]. Two common methods used in the design of ultrasonic flow meters are travel-time and Doppler techniques. Fig. 1

sketches an ultrasonic flow meter based on a dual-sensor, travel-time technique, which is the fundamental element of the more complicated multi-path flow meter.

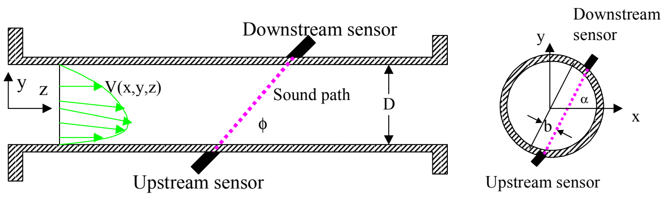

Figure 1. Schematic diagram of a dual-sensor (single cordal path) ultrasonic flow meter.

Travel-time ultrasonic flow meters measure the difference between the two opposite pulse propagation times along an ultrasonic path defined by the dual sensors. The configuration parameters for dual-sensor ultrasonic flowmeters are the path offset, b, the path azimuthal angle, α, and the path axial angle, ϕ. The basic equations for calculating propagation times in the ultrasonic flowmeter can be written as:

$$\int_1^2 dt = t_{12} = \int_1^2 \frac{ds}{C+\mathbf{V}\cdot\mathbf{e}} = \frac{s}{C+V_s}$$
$$\int_2^1 dt = t_{21} = \int_1^2 \frac{ds}{C-\mathbf{V}\cdot\mathbf{e}} = \frac{s}{C-V_s} \tag{1}$$

where $\mathbf{V}$ is the fluid velocity, C is speed of sound, $\mathbf{e}$ is a unit vector of sound path, s is path length, and V_s is the averaged fluid velocity along the sound path. Thus, from the above equations, we have the indicated velocity and speed of sound in the fluid, respectively.

$$V_I = \frac{V_s}{\cos(\phi)} = \frac{s}{2\cos(\phi)}\left(\frac{1}{t_{12}} - \frac{1}{t_{21}}\right)$$
$$C = \frac{s}{2}\left(\frac{1}{t_{12}} + \frac{1}{t_{21}}\right) \tag{2}$$

The meter response depends on the integration line of the acoustic propagation path. In general, the acoustic propagation path is not strictly a straight-line [6]. The effects of curved ray paths on meter performance have been investigated and reported elsewhere [7]. These effects diminish as the Mach number of the flow becomes small (*e.g.,* < 0.1). Because this technique determines not only the average fluid velocity but also the sound speed, the method can also be used to measure other fluid properties (such as temperature, etc.) provided that a relationship between the desired property and the speed of sound is known.

B. Traditional Ultrasonic Flowmeter

As shown in (1), the numerical simulation of an ultrasonic flow meter requires a complete description of the 3-D flow field, $\mathbf{V}$, in a pipe. Velocity fields erected from mathematical models (composed of various velocity elements) and Computational Fluid Dynamics (CFD) have been used to simulate flow meter response [7]. Using these simulated flows, various arrangements of travel-time ultrasonic sensors were tested to better understand how meter output depends on the sensor geometry and on the signal interpreting software. Fig. 2 shows a CFD simulation of an indicated velocity field for a dual-sensor flow meter with $\phi = 45°$ placed at various cordal locations, b, and orientations, α. The simulation data was obtained using CFD results five diameters downstream from a single elbow for Reynolds number of $\mathrm{Re} = 3\times10^6$ (the averaged bulk velocity normalizes the velocity). These results indicate that the dual-sensor meter response strongly depends on the meter installation orientation and location. Furthermore, these results show that large profile dependent errors could exist. The indicated velocity is ranging from 0.8 to 1.08 of the average velocity depending on sensor geometry.

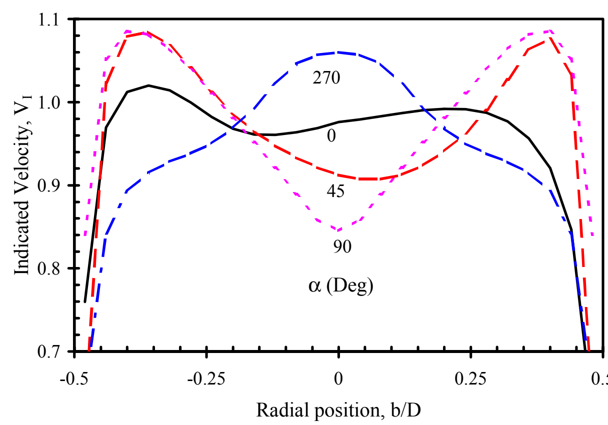

Figure 2. Simulation of a dual-sensor (single cordal path) flow meter, 5 diameters downstream from a single elbow for $\mathrm{Re} = 3\times10^6$ and $\phi = 45°$ at various cordal locations, b, and orientations, α.

There are two fundamental issues of dual-sensor ultrasonic flow meters. The first is the error due to the cross flow components. The effective velocity seen by the flow meter is

$$V_s = \mathbf{V}\cdot\mathbf{e}_s = V_x e_x + V_y e_y + V_z e_z$$
$$V_I = V_s / e_z = V_z + (V_x e_x + V_y e_y)/e_z \tag{3}$$

where V_x, V_y, and V_z are the velocity components, and e_x, e_y, and e_z are the direction cosines of the sound path, in X, Y, and Z directions respectively. When the volumetric flow rate is the main result of interest, the desired meter response is the axial velocity, V_z. However, the indicated velocity contains extra terms from the cross components, which contribute to the meter error. The effects of these cross components increase as ϕ increases or as e_z decreases. On the other hand, these installation effects can be used to measure the cross flow and swirl components in the flow, or to diagnose the flow field of a flow facility. The second issue of the dual-sensor ultrasonic flow meter is the interpretation of the area-averaged velocity from the measured line integral velocity V_I. To do the interpretation, a pipe flow profile needs to be assumed and thus the accuracy of the meter will depend on the assumed profile. Thus, installation, location, and orientation are critical to obtaining satisfactory levels of meter performance, and special caution is needed when ultrasonic flow meters are used to measure velocity in the presence of cross flows.

To improve the accuracy and reduce the sensitivity of the installation effects, flow meters with multiple ultrasonic paths have been used. The estimated averaged velocity of a multi-path ultrasonic flowmeter can be expressed as,

$$V_m = \sum_{i=1}^{p} w_i V_i \tag{4}$$

where p is the total number of ultrasonic paths, V_i is the measured mean velocity along the *i*-th path, and w_i is the integration weight factors associated with the *i*-th path. The selection of the weight factors and the placement of the ultrasonic paths have previously been done based on Gaussian Quadrature techniques that assume a ideal velocity profile inside the meter [8]. The simulation results for four typical techniques are shown in Fig. 3. These four techniques are denoted as Gauss-Legendre (Leg), Gauss-Jacobi (Jac), Gauss-Chebyshev (Chev) and "tailored" Pann.

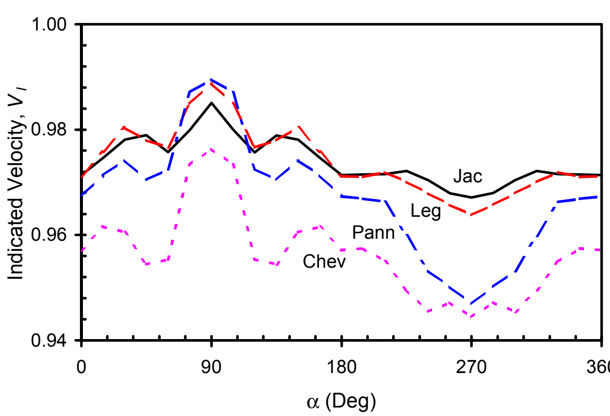

Figure 3. Simulation of a four cordal path flow meter, 5 diameters downstream of a single elbow for $\mathrm{Re} = 3 \times 10^6$ and $\phi = 45°$ for different Gaussian quadrature techniques.

As expected, more sensors lead to more information and thus the results show that multi-path flowmeters do improve the metering accuracy and profile insensitivity when compared to the single path arrangement in Fig. 2. The variation of indicated velocity with meter orientation, α, has been improved from 0.28 to about 0.04. However, in all cases, the indicated velocity is always lower than the average velocity of 1.0, and no installation angle can be found to yield the correct averaged velocity. Again, this is because the design of the transducer arrangements and the signal processing algorithms for ultrasonic flow meters have generally been based on an assumed profile and in fact, such profiles seldom occur in field applications. In addition, meter installation effects often lead to skewness and circulation velocity components that were not assumed when the meter was designed. To realize the potentials of ultrasonic technology in flow measurement and standardization, a new approach is used in this study.

III. RESULTS

A good flow calibration system requires not only the delivery of the quoted uncertainty but also the ability to access the distribution of the flow velocity profile entering the meter-under-test. The knowledge of an incoming velocity profile is a critical component affecting the performance of most flow meters. Traditional flow meters aim to achieve accuracy in average flow rates and rarely provide detailed flow field descriptions for a calibration facility. To attain such a level of detailed flow information, more complex sensing arrangements, or other novel methods for detecting varying flow fields, need to be considered.

One way to describe detailed flow fields is acoustic imaging or tomography. This is a sensing methodology where the response of a large array of ultrasonic sensors is used to reconstruct the 3-D velocity profile present in the flow meter. In theory, acoustic tomography provides an attractive procedure for sensing a complex time-dependent flow field given the non-intrusive nature of its detection and the completeness of its results. However, there are still many practical problems to the implementation of such sensing systems. The limited resolution of ultrasonic travel-time and ray spacing are two such problems. Unlike the scalar problem, the signal for acoustic tomography depends not only on the magnitude but also on the relative orientation of the rays to the vector field. Thus, measuring time difference over a continuum of angles on a plane does not yield sufficient data to recover the unknown vector. At present, this approach can lead to non-unique results and poor time resolution; thus a more practical solution is necessary.

An Advanced Ultrasonic Flow Meter

We propose a pseudo-tomographic deconvolution technique for the development of an intelligent ultrasonic flow meter capable of evaluating the flow velocity profile in real time. This meter would make use of a customized ultrasonic multi-path array to acquire accurate flow measurements and provide details of the flow profile in the pipe.

As discussed before, one adverse result of traditional multi-path ultrasonic flow meters is that deviations from the assumed profile may lead to errors in the estimation of the volumetric flow due to the inadequacy of the postulated weighting factors, w_i (see equation 4). One way to overcome this problem is by applying flow profile correction factors, C_i, to each acoustic path based on the encountered velocity profile. Making such corrections, (4) becomes,

$$V_m = \sum_{i=1}^{p} C_i w_i V_i \qquad (5)$$

Unfortunately, the selection of the C_i's is unique for each velocity profile, which is typically unknown, and this leads to a problem of immense proportions – especially if treated experimentally. On the other hand, if the velocity profile at the meter is known, it is theoretically possible to predict such correction factors. Following this approach, the main task is to estimate or determine the type of the velocity profile to which the flow meter is exposed.

The pseudo-tomographic deconvolution technique proposed above could be implemented using pattern recognition algorithms. One could make use of a modified back-propagation method to create the electronic brain for the AUFM. Figure 4 schematic shows a diagram of an AUFM, which consists of conventional multi-path ultrasonic flow meter hardware (UFM) plus flow field recognizer software (FFR). The FFR is based on a partitional pattern classifier program that was developed originally for speech recognition applications [9]. The internal workings of the FFR require three main operations: (a) selecting training and testing data relevant to the classification process, (b) formulating a memory matrix, and (c) applying the memory matrix to new data for real-time classification.

As with most other pattern classification algorithms, the FFR association matrix is established through a training process. The training process consists of inputting a series of feature-vectors (*i.e.,* the responses of the sensing array) along with each vector's corresponding response category (*i.e.,* the desired sensing system output). The pattern recognition algorithm will map a vector of real-valued variables (*e.g.,* ultrasonic multi-path velocities) into a finite set of arbitrary categories or classes (*e.g.,* patterns or types of velocity profiles). The input vector represents the patterns and features that need to be classified or recognized by the algorithm. Training and testing is required to find a set of parameters that yield the highest level of recognition performance and the minimum level of uncertainty. Based on the trained memory, the recognizer would be able to take the input as a previously unknown vector and produce as output a list of "candidate" categories, each with an assigned probability of the likelihood that the selected class represents the unknown input vector.

Once the flow field patterns are estimated, the information on the class probability will be used to quantify the velocity profile enabling the AUFM to make adjustments in order to provide accurate meter readings. The application process is very fast, lending itself for the classification of ultrasonic signals in real time. Using this approach, the final corrected meter output for the volumetric flow rate can be estimated as:

$$V_{AF} = \sum_{J}^{N} P_J \sum_{i=1}^{p} C_{Ji} w_i V_i \qquad (6)$$

where N is the number of flow classes or categories selected, P_J is the probability that the meter output vector V_i belong to the *j*-th class (category), and the C_{Ji} is the correction constant for the *i*-th sensor for the *j*-th class flow. The correction constants, C_{Ji}, are determined when the finite number of flow patterns to be considered is selected. Therefore, the set of meter constants found by this technique is a function of the unknown flow field in contrast with the prescribed set of meter correction factors used by the traditional meters.

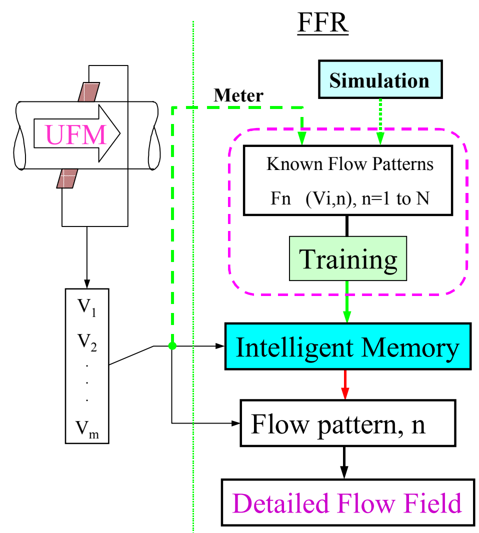

Figure 4. A schematic diagram of an advanced ultrasonic flow meter. Fn denotes the selected flow patterns. For each n, there is a set of velocity Vi and the class parameters.

The pattern recognition approach yields many advantages over tomographic deconvolution mathematics. First, the time required for flow field classification is less than that required for deconvolution of tomographic data because no matrix inversion is required. Second, pattern recognition methods are designed to establish robust associations between sensor data and response classes which makes them less sensitive to noise that could otherwise hinder tomographic deconvolution. Third, the use of pattern recognition methods requires no physical knowledge of the process being classified – only cause-effect relations need to be known. Using the FFR, the AUFM could be an improvement over current flow meter technology because it is able to recall past flow information, much like any person is able to use previous experience for future reference. Meanwhile, traditional meters are based only on the knowledge available at the time of their design.

B. Test Result

The key to the success of the classification process resides in the ability of the selected sensor arrangement to provide a feature-vector with enough information to perform the classification. For example, suppose that the AUFM had only one ultrasonic sensor pair. Then, it would be difficult for the FFR to yield the correct selection of the flow category, even in symmetric flows, given that the sensing arrangement cannot provide enough information to discern differences between the various profile categories. However, if the AUFM had a multitude of cordal paths –in relevant locations– the FFR may be capable of discerning the differences between the velocity profiles and providing the correct meter constants for each case of interest.

Our current AUFM is based on a Daniel Senior Sonic gas flow meter [10]. It is 20-cm (8") in diameter and has 4-paths arranged in a x-pattern per Gauss-Jacobi quadrature specifications. Prior to training, the data read by the FFR program was organized in lines containing the feature-vector *(i.e.,* the V_i's) followed by the vector's corresponding response category *(e.g.,* fully developed flow, elbow flow, reducer flow, etc.) and other related parameters (*e.g.,* calibration constants, C_{Ji}). In our approach, the output of a conventional multipath flow meter consists of an array of path-averaged cordal velocities *(i.e.*, indicated velocities), V_i's, which were provided to the flow field recognizer. The flow field recognizer made use of machine-learned concepts to determine the association between the V_i's and the selected flow classes.

Both simulation and experimental data were used to evaluate the performance the AUFM. The simulation data was generated using both mathematical and CFD models [7] coupled with a model of the ultrasonic sensor response expected from the selected four-path meter configuration. Experiments were conducted in an open-ended gas flow facility. The facility consisted of a blower located at the downstream end of the 20-cm (8") diameter pipe, which pulled flow though the four-path UFM. The UFM was installed about 30 diameters upstream from the blower.

Table 1 lists the flow categories selected for three groups used in testing the performance of the four-path AUFM. Group-I, which consist of 14 flow classes, is based on the meter simulation using mathematical models, which are composed from various velocity elements [7]. Group-II consists of 12 flow classes from the combination of CFD and mathematical models. Group-III consists of 11 experimentally acquired flow classes.

In the group-I column, Uniform represents pure 1-D plug flow; Laminar represents classic parabolic, axial velocity profile; BM is a typical fully developed profile given by Bogue and Metzner [11]; PL25 is a power law profile with the exponent of 1/25; fr2 is a velocity field having a slow center core profile; SL is a simulation of a typical single elbow flow, which is a combination of a power law profile, a set of double vortex eddies, and a skew axial velocity flow; and DL is a simulation of a double elbows out-of-plane flow, which results from the combination of a power law profile, a "fr2" slow center core profile, and a single vortex eddy. The classic Taylor vortex model [12] was used to simulate the typical cross or swirl flows commonly found in the elbow flows. In group-II, Lxy denotes the CFD result for double elbows out of plane; and Ly for a single elbow. In the table, z denotes the axial distance downstream of a pipe element (elbow or reducer). In group-III, different types of mechanical blockages were mounted on the piping entrance four diameters upstream of the UFM to create various flow fields. Their names are meant to be self-explanatory.

Table 1. Flow categories selected for three test groups.

Class	I. Math, N=14	II. CFD , N=12	III. Experimental, N=11
0	Uniform	Uniform	Straight pipe
1	Laminar	BM	Single elbow at 0°
2	BM	Reducer, z=6, 0°	at 90°
3	PL25	z=50, 0°	at 270°
4	Fr2	Lxy, z=6, 0°	Half of pipe at 0°
5	SL, 0°	z=56, 0°	at 90°
6	45°.	Ly, z=5, 0°	at 180°
7	90°.	z=5 , 90°	at 270°
8	135°.	z=5, 180°	1/4 of pipe at 90°
9	180°	z=5, 270°	at 270°
10	225°	z=55, 90°	plate blocks center pipe
11	270° .	z=55, 270°	----
12	315°	----	----
13	DL	---	----

To simulate the AUFM time series output, a set of random numbers was created for each selected flow case, based on the ultrasonic response expected from the four-path sensing configuration. A normal distribution function was used for the random number generator. The uncertainty in the recognition process depended on: (a) the ability of the UFM sensor array to measure the quantity of interest *(i.e.,* features selected for recognition), (b) the uniqueness of the input-output transformation *(i.e.,* separability of the classification process), and (c) the number and relevance of the training exercises provided to the flow field recognizer.

Figure 5 shows the sample data of the experimental results for the group-III case. The data on the left are the pattern data used to train the FFR. The data is shown as an ensemble of the V_i's obtained from each sensing path in the UFM for each of the 11 unique classes – each path depicted in a different symbol. A sample test data input vector is shown on the right. Making a visual inspection, it is apparent that the sample set belongs to class-7 flow field. During the test, the FRR predicted class-7 with a probability of 1.0.

To test the effects of the sensor uncertainty and the ability of the AUFM to differentiate the flow patterns, different values of standard deviations were used in generating the random numbers. For a standard deviation of 1% of the velocity vector (not uncommon in real applications), the probability that the FFR makes a correct classification of a test flow pattern is about 95% for the groups I and II sets. The correct probability decreases as the standard deviation of the data is increased. Results showed that the correct probability, and the ability to find a correct flow pattern, decreases as the number of the flow patterns available increases. The effects of velocity uncertainty in the sensors are also noticed in the experimental test on group-III. The number of flow classes and quality of the training data constrain the ability of the FFR. In order to have good classification results for the selected flow patterns, we must reduce the uncertainty of the velocity sensor data. Averaging the raw data taken directly from the UFM over longer periods of time helps. In this work, a 60-second time average was selected for the velocity average. During this investigation, problems with the large velocity variations were due to the large time variations introduced by the poorly controlled test facility. A more stable flow facility might be able reduce most of the meter uncertainty issues.

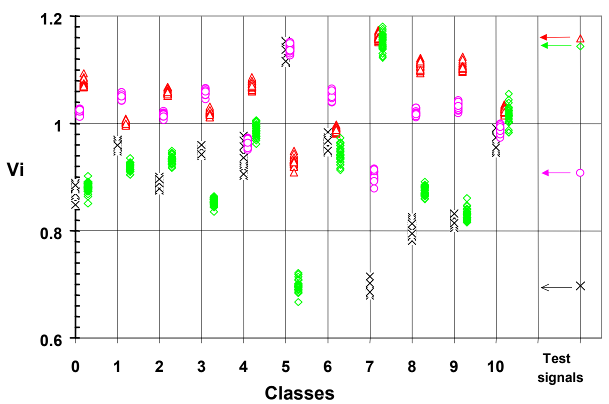

Figure 5. Sample data of a tested FFR for group-III.

With the ultrasonic 4-path array, we were able to teach the AUFM how to differentiate between 14 different flow profile classes with a success rate of 95% or better. Some profiles are indistinguishable, and thus, the FFR failed. However, if there were some separable feature in the velocity sensor vector, the FFR would repeatedly select the correct candidate. In the case where the desired output from the AUFM would be a quadrant-based description of the flow field, the ultrasonic sensor arrangement would need to be more complex *(e.g.*, 8 to 12 sensor pairs may be required). For such an application, the feature-vector would be enlarged in proportion to the increase in sensor pairs. The response category would need to become more complex to accommodate the detailed description required.

IV. SUMMARY

A design for an advanced ultrasonic flow meter has been discussed. The main feature of the AUFM is its use of a flow field recognizer to make detailed determinations of the flow field properties taking advantage of pattern recognition technology. A training process for the flow field recognizer was discussed and its application for the determination of volumetric flow rate has been provided. This paper shows how *a priori* knowledge of the meter sensor array could be used in an FFR to optimize the capability of the AUFM. These results helped in the development of an "intelligent" flow sensor capable of detecting adverse installation effects in order to make adjustments and provide accurate flow rate measurements.

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DISCLAIMER

Identification of specific commercial products is made for technical completeness but does not constitute an endorsement, nor does it indicate that the products are preferred for the application.

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