The Development of Gas and Water Pipe Discrimination Equipment based on Thermal Conduction and Brain Computing

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ABSTRACT

Gas and water companies conducting inspection and replacement of pipes laid under public roads must be able to accurately determine whether the metallic pipes that they uncover are gas pipes or water pipes. At present, the fluid (water or gas) contained within the pipes is generally identified using either percussive inspection techniques, or by opening a small hole in the pipes and directly checking the fluid contained within. However, in applying these methods potentially hazardous damage may occur to pipes other than the target pipe, and furthermore percussive inspection techniques in particular lack discriminative reliability.

Saibu Gas Co., Ltd. has therefore developed a new gas and water pipe discrimination device that relies on completely different fundamentals to the above-mentioned techniques, and instead utilizes the thermal conductivity characteristics of the pipe surface. The specialist skills and training required to use the new equipment are minimal, and accurate discriminative testing can be performed safely by anyone, without the risk of damaging piping.

In this paper, the author outlines the main activities involved in the development of the new equipment. The main topics covered are the development of discriminative techniques based on heat conduction; the development of the brain-computing method for high precision discrimination of heat conduction data; and the development of a controller loaded with the discriminating algorithm.

INTRODUCTION

When conducting inspections and replacing gas and water pipes laid under public roads, it is necessary to accurately determine whether the metallic pipes uncovered are gas pipes or water pipes. However, it is often difficult to discriminate between gas and water pipes because they are constructed using similar materials, have a similar shape, and are often laid at the same location.

A number of discriminative methods already exist, for example, making a small hole in the pipe and sampling the fluid directly, or performing percussive inspections. The former is a direct and reliable method but there is a risk of drilling or accidentally damaging pipes other than that intended. Moreover, discrimination by this method sometimes takes time and may lead to substantial delays in pipeline repair and construction work. The latter method requires a skilled operator and sometimes lacks reliability. Another method, which involves the use of supersonic waves, has also been proposed, but it is neither practical nor suitable for application at the site of construction due to the size of the equipment required and the fact that highly qualified and experienced personnel are needed to operate it.

Saibu Gas Co., Ltd. has solved the above-mentioned problems by developing new equipment to distinguish between gas and water pipes. This new equipment relies on completely different fundamentals to the methods used at present, and is based on a new technique that utilizes the thermal conductivity characteristics of the pipe surface. In this paper, the author outlines the main activities involved in the development of the new equipment. The main topics covered are the development of discriminative techniques based on heat conduction; the development of the brain-computing method for high precision discrimination of heat conduction data; and the development of a controller loaded with the discriminating algorithm.

HEAT CONDUCTION BASED DISCRIMINATIVE TECHNIQUES

The heat conduction method that is applied as the discriminative technique in the new equipment is based on the fundamental concept that the heat capacity of a pipe, and therefore the thermal conductivity properties at its surface, vary depending on the liquid contained within the pipe. The method consists of detection techniques for thermal conductivity characteristics, and discrimination based on the thermal conductivity ratio.

Detection Techniques for Thermal Conductivity Characteristics

Establishing a Method of Detecting Thermal Conductivity Characteristics. To distinguish between fluids contained within metallic pipes, it is necessary to identify a common distance (on the surface of the gas or water pipe) relative to the position of the heat source, at which the effects of thermal conduction can be clearly distinguished. Figure 1 shows the correlation between the surface temperatures of typical gas and water pipes, and the distance of heat conduction from the heat source. The effect of the heat source is too large at positions close to the heat source, and conversely too small at positions far away from the heat source (see the shaded region). Trials conducted by the author have shown that a distance of 20 mm from the heat source provides an optimum location, at which the differences in the effects of thermal conduction in both gas and water pipes can be clearly identified without the any direct effects from the heat source.

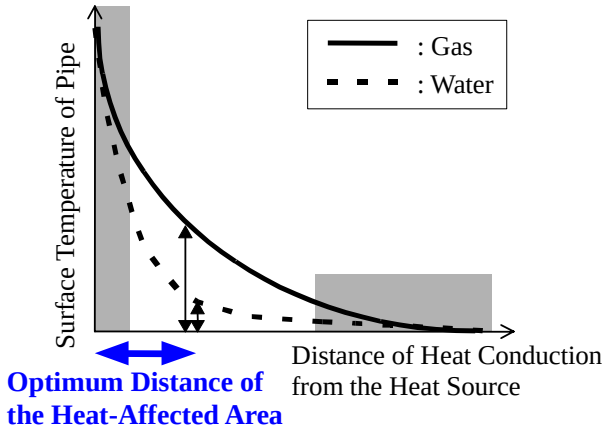
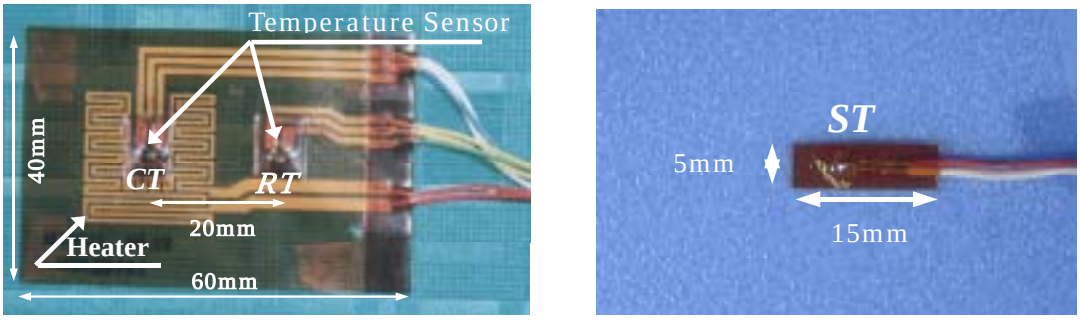


Figure 1. Correlation between the Pipe Surface Temperature and the Distance of Heat Conduction from the Heat Source

Heat Conduction Sensor Development. Based on the heat conduction sensing techniques described above, the optimum temperature sensor configuration for measuring the temperature of the heat affected area on the pipe surface was investigated, and a heater design created that has a shape capable of shortening the time required to heat the pipes. The temperature sensors and the heater were combined to form the all-in-one laminated design (shown in Figure 2) by placing them between thin sheets. The same kind of laminate structure has been adopted for the heat sensor that is used to measure the reference temperature. Figure 3 shows the arrangement used to detect the heat conduction characteristics.



(a) Heat Conduction Sensor (b) Reference Temperature Sensor

Figure 2. Heat Conduction Sensors

Table 1. Names of Parts and their Functions

Part Name	Functions
Heater	A heat source of the appropriate heat capacity that is shaped such that metallic pipes of a large heat capacity can be efficiently heated from the surface.
Sensor for measuring the temperature at the center of the heated area (*CT*)	This sensor is located at the center of the heater, and efficiently measures the increase in pipe surface temperature at the center of the heated area.
Sensor for measuring the temperature of the heat-affected area (*RT*)	This sensor is located at the optimum distance from the center of the heater, and efficiently measures the increase in pipe surface temperature at the heat affected region formed due to conduction of heat through the pipe as opposed to the direct effects of the heater.
Reference temperature sensor (*ST*)	This sensor is located at a position where the effects of the heater are negligible, thereby providing a reference measurement of the pipe surface temperature.

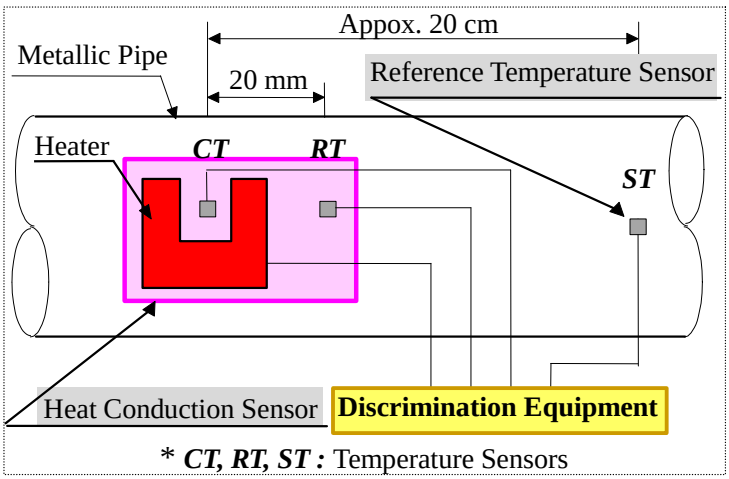


Figure 3. Arrangement used to Measure the Heat Conduction Characteristics

Discrimination Method Based on the Thermal Conductivity Ratio.

Equation (1) shows the relationship between the thermal conductivity ratio R(k) and the thermal conductivity data measured at the surface of the pipe by the heat conduction sensors and the reference temperature sensor. As shown in Figure 3, *CT*, *RT* and *ST* refer to the temperature measured at the center of a heater, the temperature at a point 20 mm away from the heater, and the reference temperature, respectively. $CT(k)$, $RT(k)$ and $ST(k)$ are the temperatures measured at a time k after heating.

$$R(k) = \frac{RT(k) - ST(k)}{CT(k) - ST(k)} \times 100(\%) \qquad (1)$$
$$k : \text{Heating time}[0 \le k \le 10(\text{min})]$$

Figure 4 shows the relationship between the thermal conductivity ratio and the heating time. Although both gas and water pipes appear to follow a similar trend, the markings in Figure 4 show that notable differences in the data distribution patterns can also be observed. This result suggests that heat conduction data can be used for discriminative testing.

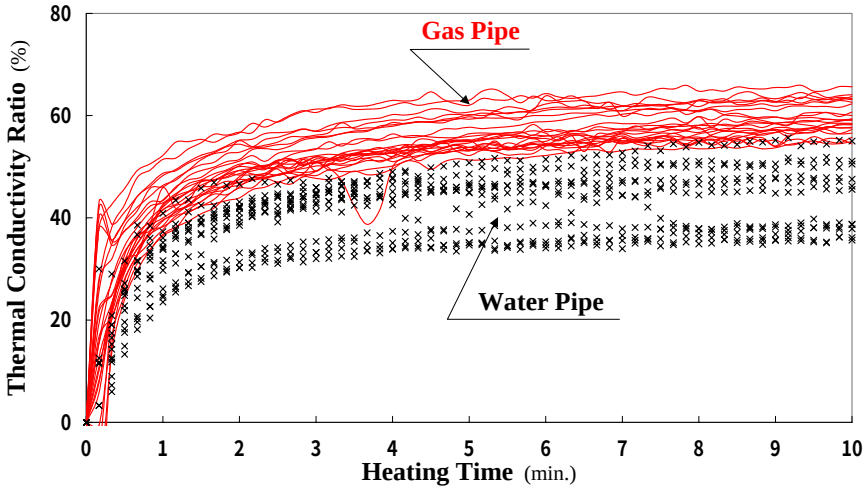


Figure 4. Relationship between the Thermal Conductivity Ratio and the Heating Time for Gas and Water Pipes

DISCRIMINATION BASED ON BRAIN COMPUTING

Brain computing is an advanced processing method formed by the fusion of supervised self-organizing maps and fuzzy template matching. The method allows pattern classification of data that cannot be discriminated accurately using classical methods.

Supervised Self-Organizing Maps

Supervised self-organizing maps are the advanced result of combining self-organizing maps, which are a kind of neural network, with LVQ (learning vector quantization). The supervised self-organizing maps technique implements efficient learning for data classification in cases where both the number of original data patterns (which act as the supervisor) and the number of patterns to be classified are known.

Figure 5 shows a brief outline of the supervised self-organizing maps procedure. Here, $X^{c_r}(t) \in R^s$ and $W_{ij}^{c_r}(t) \in R^s$ are defined as follows:

$X^{c_r}(t)$: The input vector $(r = 1,2,\cdots,n)$ belong to class c_r

$W_{ij}^{c_r}(t)$: The weight vector $(i = 1,2,\cdots,l),(j = 1,2,\cdots,m)$ in unit (i, j) on the competing layer belonging to class c_r.

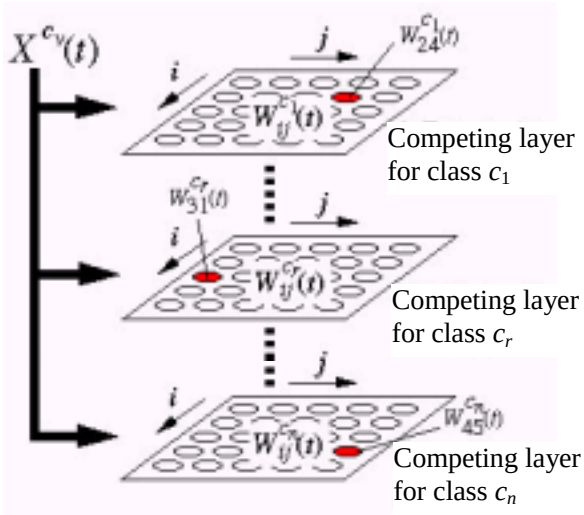


Figure 5. Competing Layers

The initial value of the weight vector $W_{ij}^{c_r}(0)$ is set randomly when the learning algorithm is initiated. In each learning cycle, the winning weight vector $W_{ij}^{c_r}(t)$ selected from the competing layer of each class is updated along with the vectors adjacent to it. If the class c_v of the input vector $X^{c_v}(t)$ and the class c_r of the weight vector $W_{ij}^{c_r}(t)$ are equal $(r = v)$, then the update procedure is performed in accordance with equation (2). If the two classes are not equal $(r \neq v)$, then the update procedure is performed in accordance with equation (3). In both equations (2) and (3), $\alpha(t)$ is defined as a learning factor which decreases monotonically over time t. The $\beta(t)$ term, which is present in equation (3), is an adjustment factor for the learning factor $\alpha(t)$ that is used if the classes are different, and this increases monotonically over time t. $(p,q) \in D$ represents an adjacent area of a winning unit and decreases over time t.

$$W_{pq}^{c_r}(t+1) = W_{pq}^{c_r} + \alpha(t)\{X^{c_v}(t) - W_{pq}^{c_r}(t)\} \tag{2}$$

$$W_{pq}^{c_r}(t+1) = W_{pq}^{c_r} - \alpha(t)\beta(t)\{X^{c_v}(t) - W_{pq}^{c_r}(t)\} \tag{3}$$

In the initial stages of learning, the adjustment factor $\beta(t)$ in equation (3) is small and as a result the updated weight is close to the initial weight. However, as learning

progresses $\beta(t)$ increases monotonically and the weight vector gradually learns to deviate from the input vector.

The introduction of $\beta(t)$ means that the supervised self-organizing maps carry out self-organizing map learning in the initial stages, and learning vector quantization type learning in the closing stages. In other words, the discrimination rate for similar adjacent patterns is improved by precisely maintaining the characteristics of the target pattern and learning to move away when appropriate from patterns that we do not want to discriminate. Figure 6 shows the learning results obtained using supervised self-organizing maps.

To be more precise, the input pattern has components of heating time k and thermal conductivity ratio $R(k)$, so the input vector X^{c_r} and weight vector $W_{ij}^{c_r}$ are both two-dimensional vectors. When considering gas and water pipes we are considering two classes, and 5 × 5 units are allocated to the competing layers. Typical thermal conductivity ratio data for both gas and water pipes is used as training data (supervisor data). For each cycle of the supervised self-organizing maps learning procedure, a randomly selected heating time k, and the thermal conductivity ratio $R(k)$ of gas and water pipes at that time are used as inputs of the network. The learning cycle was repeated ($T = 1000$ times), where one learning cycle is comprised of learning via both gas pipe and water pipe vector input.

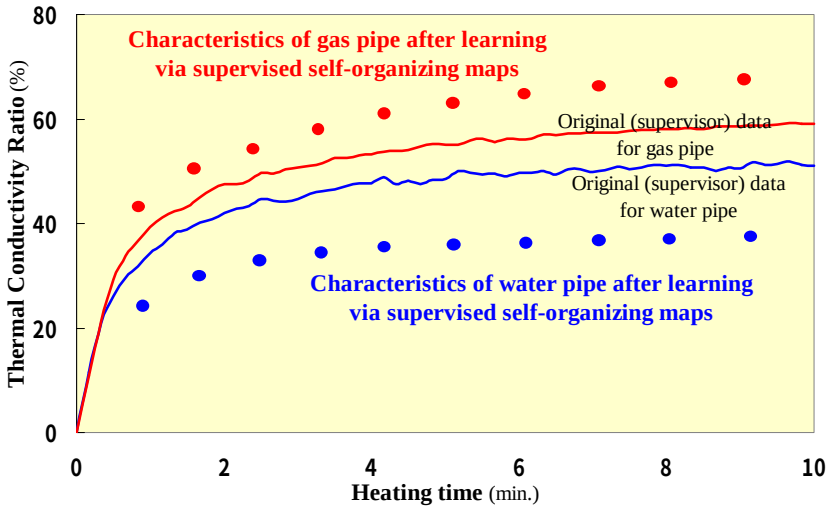


Figure 6. Learning Results Obtained using Supervised Self-Organizing Maps.

Fuzzy Template Matching

Fuzzy template matching is a procedure for performing pattern classification by comparing the matching grade of data with fuzzy templates which are created based on the characteristics of the patterns of each class, which are in turn self-organized depending on the unknown input pattern and the supervised self-organizing maps.

The following is a brief overview of the fuzzy template matching procedure.

First, a fuzzy template $F_{ij}^{c_v}(X)$ centered on each weight vector $W_{ij}^{c_v}$ of each competing layer is created for each unit (i, j) in accordance with equation (4).

$$F_{ij}^{c_v}(X) = \exp\left\{-\gamma\eta^{c_v}(X)\left(\left\|X - W_{ij}^{c_v}\right\|^2\right)\right\} \tag{4}$$

Where γ is a basic rate of decrease (0.01), and $\eta^{c_v}(X)$ is a parameter to adjust γ in the X space. By introducing the term $\eta^{c_v}(X)$, the number density of all weight vectors in the X space is reflected in the rate of decrease. If the rate of decrease were a constant γ, then the fuzzy template would display isotropy, however due to the introduction of the term $\eta^{c_v}(X)$, the fuzzy template will display anisotropy.

The term $\eta^{c_v}(X)$, which is used for adjusting the rate of decrease, can be calculated as follows:

First calculate the relevant value of $f_{ij}^{c_r}$. For weight vectors for class c_v, that is $W_{ij}^{c_v}(r = v)$, use equation (5). For weight vectors for any other class $(r \neq v)$ use equation (6). Substitute the value of $f_{ij}^{c_r}$ into equation (7) and calculate the value of $\eta^{c_v}(X)$.

$$f_{ij}^{c_r} = \exp\left\{-\gamma\left(\left\|X - W_{ij}^{c_r}\right\|^2\right)\right\} \tag{5}$$

$$f_{ij}^{c_r} = -\exp\left\{-\gamma\left(\left\|X - W_{ij}^{c_r}\right\|^2\right)\right\} \tag{6}$$

$$\eta^{c_v}\left(X\right) = 1 - \frac{\sum_{i=1}^{l}\sum_{j=1}^{m}\sum_{r=1}^{n} f_{ij}^{c_r}\left(X\right)}{\max\limits_{x}\left(\sum_{i=1}^{l}\sum_{j=1}^{m}\sum_{r=1}^{n} f_{ij}^{c_r}\left(X\right)\right)} \tag{7}$$

Use equation (8) to obtain the fuzzy template $T^{c_v}\left(X\right)$ of each class. The unknown input vector $X^{c_r}\left(k\right)$ $\left(k = 1,2,\cdots,N\right)$ is classified as Class I (having the largest cumulative matching grade) by equation (9).

$$T^{c_v}\left(X\right) = \sum_{i=1}^{l}\sum_{j=1}^{m} F_{ij}^{c_v}\left(X\right) \tag{8}$$

$$I = \arg\max_{v}\sum_{k=1}^{N} T^{c_v}\left(X^{c_r}\left(k\right)\right) \tag{9}$$

Fuzzy templates for the discrimination of gas and water pipes are created by combining all the fuzzy templates that are created based on each weight vector learned using supervised self-organizing maps (see Figure 7). The fuzzy template patterns shown in Figure 7 are elongated in the direction of the time axis, and the matching grade can be observed to decrease drastically on the sides where different patterns are located. These characteristics allow discriminative analyses to be performed in a shorter time than for isotopic fuzzy templates.

To perform the final discriminative analysis, thermal conductivity data measured at regular time intervals is applied to the fuzzy templates that have been created for the discrimination of the gas and water pipes under consideration, and the cumulative matching grade for each template is calculated and compared sequentially.

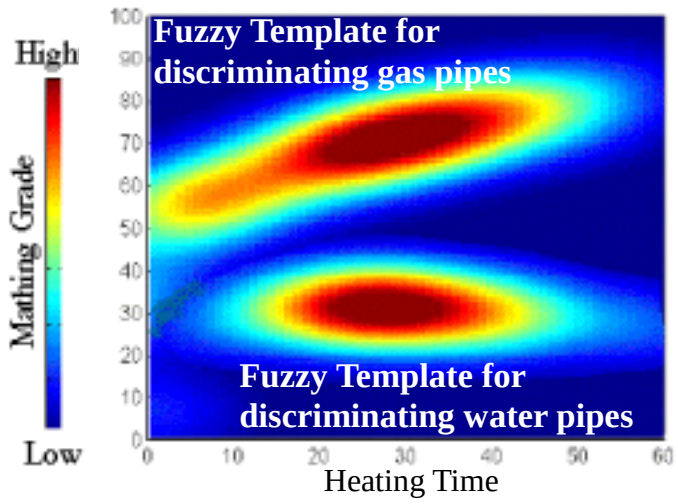


Figure 7. Fuzzy Templates

Discrimination Results

Figure 8 shows discriminative analysis results obtained using T^{GAS} and T^{WATER} that were created based on measured thermal conductivity data. By using the innovative learning algorithm and fuzzy template matching that result from the fusion of supervised self-organizing maps and vector quantization, the technique allows relatively similar and adjacent pipe categories to be distinguished. In effect, we have established a discriminative method that is not affected by data non-linearity and on-site noise.

Cumulative matching grades calculated based on T^{GAS} : $\sum_k T^{gas}(X(k))$

Cumulative matching grades calculated based on T^{WATER} : $\sum_k T^{water}(X(k))$

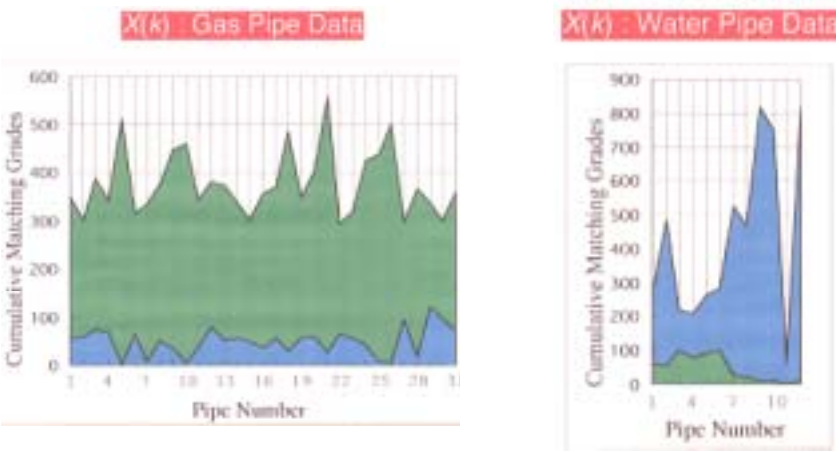


Figure 8. Discrimination Results

GAS AND WATER PIPE DISCRIMINATION EQUIPMENT

The gas and water pipe discrimination equipment consists of a controller for arithmetic processing; heat conduction and reference temperature sensors for detecting the thermal conductivity characteristics on the pipe surface; and a battery for heating.

Specifications

Figure 9 shows a photograph of the controller, and Table 2 shows a summary of its specifications.

Figure 9. Controller for the Gas and Water Discrimination Equipment

Table 2. Specifications of the Equipment

Item	Application Range
Applicable pipe/bore	Cast iron pipe: 100, 150, 200, 250, 300 (mm) Steel pipe: 25, 32, 40, 50, 80 (mm)
Time required	3 – 10 minutes
Display type	Liquid crystal display bar graph
Interval of discrimination	Every 5 seconds
Weight	660g
Dimensions	W110×D45×H220（mm）
Power source	12V battery

Performing Discriminative Analysis

Work Procedure (Figure 10).

(1) Use the specified cables to connect the sensors and the battery to the controller.

(2) Clean the surface of the target pipe. Apply a high heat conductivity oil compound to the heat conduction sensors, and then arrange them on the target pipe.

(3) Input the diameter of the target pipe into the controller.

(4) Perform measurements every 5 seconds.

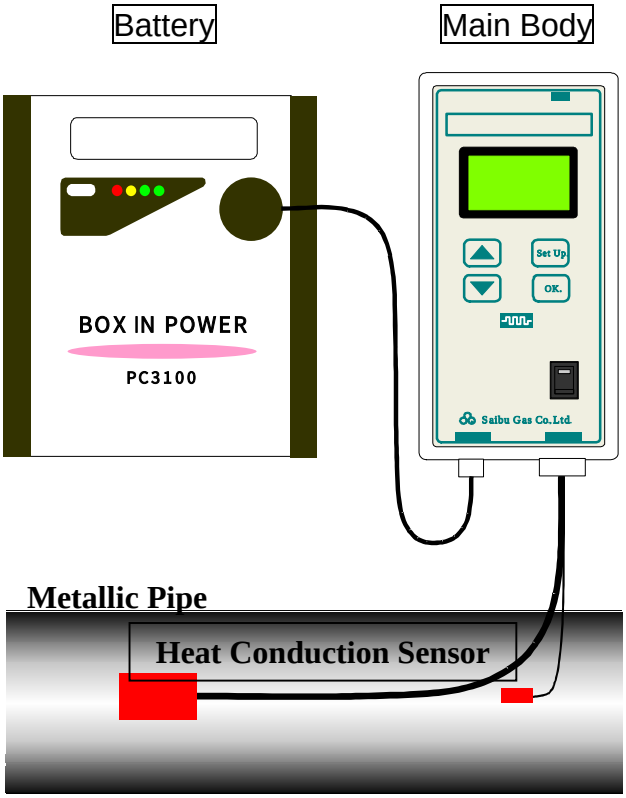


Figure 10. Discrimination Controller and Method of Application

Display of the Results. Figure 11 shows the screen of the controller while the measurements are being carried out, and Figure 12 shows the screen when measurements are completed. Operators compare the size of the bar graphs to judge whether the fluid in the pipe is gas or water.

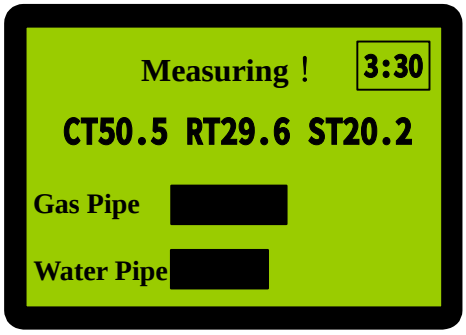


Figure 11. Screen while measurements are being carried out

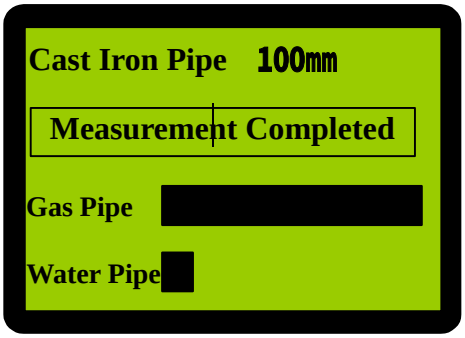


Figure 12. Screen showing a completed measurement

CONCLUSIONS

This paper has established a discriminative theory based upon heat conduction methods, and demonstrated that increased discriminative precision can be obtained by processing heat conduction data using the brain computing method. The development of a controller loaded with the discriminative algorithm relevant to this task has also been presented.

The discriminative equipment developed is simple to use, requiring neither specialist training nor technical skills for its operation, and it thereby allows operators to perform high precision discriminative assessments of gas and water pipes not only safely but also efficiently, and without the risk of damaging pipes. We hope that these studies and this equipment can offer an efficient, safe, and attractive solution to those working in other industries as well as both the gas and water industries.

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