AN INVARIANCE TRANSFORMATION TECHNIQUE FOR INTERPRETING IMAGES OBTAINED FROM UNKNOWN OPERATIONAL CONDITIONS

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ABSTRACT

This paper will focus on developing invariant pattern recognition algorithms for a class of parametric variations that are a significant cause of image transformations – variations in image gray level that occurs as a result of inadequate control of the imaging system. Situations such as these occur in many industrial applications – the one discussed in this paper is the magnetic imaging of gas pipeline faults. A general invariance transformation algorithm is developed and successful applications of the procedure are presented for the following two cases. The algorithm is first applied towards compensating for gray level variations in experimental signals obtained from gas pipeline inspections. The technique is then exercised with synthetic images to determine its ability to compensate for the effects of a "classical" image transformation – image scaling that occurs as a result of camera-object relative position. The results demonstrate that this invariance transformation technique can be applied effectively towards both types of image transformations.

1. INTRODUCTION

The development and application of invariant pattern recognition algorithms has been the focus of a significant number of image/object recognition techniques. Many of these methods deal with the "classical" invariants to compensate for the effects of camera-object relative translation, rotation and scaling. However, there exists yet another class of parametric variations that are a significant source of image transformation. These occur in a number of industrial situations when there is inadequate control of the actual test parameters associated with the imaging operation. For example, during the in-line inspection of gas pipelines, magnetic images of the pipe-wall are obtained by magnetizing the pipe. The images that are obtained depend on the magnetizer strength, orientation and location of the sensor, etc. Any and all of these cannot be controlled precisely in an actual test situation; in fact the exact values of these parameters are seldom known. Similar effects occur in remote sensing applications, imaging of components on an assembly line, etc. Such random and poorly defined parametric variations are reflected in the gray level values of the image. These effects must be compensated for, if any meaningful interpretation of the image is desired – for example, the magnetic image of a pipe-wall fault represents the fault depth and severity.

A general algorithm for compensating for such unknown or imprecise variations has been developed [1,2]. In this paper, some application results are presented for two situations. The algorithm is applied for compensating the effects of gray-level variations in magnetic images of gas pipeline faults that occur due to poor control of the imaging test parameters. The versatility of the algorithm is demonstrated by applying it towards compensating for the effects of a "classical" image transformation – image scaling that occurs as a result of camera-object relative position.

This paper is organized as follows. The invariance transformation algorithm is described in Section 2. In Section 3, results of applying the algorithm to compensate for parametric variations in experimental and synthetic images are shown. Finally the major findings are summarized and future work in this area is indicated.

2. INVARIANCE TRANFORMATION

The objective of the invariance transformation is to isolate information relating to the object (geometry and gray level) irrespective of the operational parameters associated with the imaging process. The algorithm should not only compensate for these variables, but also ideally, be able to operate without a precise knowledge of these variables. Such algorithms are, in fact, a part of many biological systems. For example, the human visual system is able to estimate the size of an object, regardless of its distance from the observer (obviously within a certain range of distances). The visual system accomplishes this by making two measurements, one with each eye. These two measurements are dissimilar and this dissimilarity is exploited in the visual cortex for synthesizing the composite 3-D view of the object, along with fairly accurate estimates of its size. The key process that allows for distance-invariant object size estimation is the fact that the image seen by each eye differs slightly from the other. This procedure can be modeled mathematically, and a generalization of the mathematical procedure can be developed for performing parameter-invariant

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image characterization. Two dissimilar "views" of the test specimen can be obtained by utilizing the two inspection modalities. The invariance transformation is an algorithm that can combine disparate signals by selectively promoting desired parametric variations (e.g. object geometry related changes) and suppressing unwanted ones (operational procedure related changes).

A transformation that combines disparate signals can be designed when the signal interpretation problem is recast as a problem in the interpolation of scattered multidimensional data. The field of computational mathematics is rich with sophisticated techniques for data interpolation. Of all these techniques, feed-forward neural networks have triumphed as the ones possessing the widest range of application. These include multiquadric surface interpolation, as in a radial basis function (RBF) networks [3] fuzzy inference systems (FIS) [4] and wavelet transform based networks (WaveNets) [5]. The key requirement for designing an invariance transformation procedure is a set (consisting of at least two) signals that originate from the same process.

Given two signals, X_A and X_B, characterizing the same phenomenon, two distinct initial features, $x_A(d, l, t)$ and $x_B(d, l, t)$, are chosen, where t represents an operational variable (for instance, camera orientation) and d and l represent geometrical parameters (for instance, angle and length, respectively). x_A and x_B are chosen such that they have dissimilar variations with t. A systematic procedure is developed to obtain a feature, h, which is a function of x_A and x_B and invariant to the parameter, t. For simplicity, x_A and x_B are considered to be dependent on only three parameters d, l and t. We need to find a function, f, such that

$$f\{ x_A (d, l, t), x_B (d, l, t)\} = h(d,l) \qquad (1)$$

Given two functions g_1 and g_2, a sufficient condition to obtain a signal invariant to t can be derived as

$$h(d,l) \blacklozenge g_1 (x_A) = g_2 (x_B) \qquad (2)$$

where $\blacklozenge$ refers to a homomorphic operator. Then the desired t-invariant response is defined as

$$f(x_A, x_B) = g_2 (x_B) \blacklozenge g_1^{-1}(x_A) = h(d,l) \qquad (3)$$

To implement this procedure, the functions h, g_1 and g_2 need to be obtained. Since h is a user-defined function, it can be chosen conveniently; for example, a linear combination of d and l. The function g_2 could be used to serve as a "conditioning" function, chosen to better condition the data. For example, if x_B contains widely spread values, g_2 can be chosen to be a logarithmic function. Having chosen h and g_2 arbitrarily, a suitable functional form is assumed for g_1, whose coefficients are to be determined. This is done by solving a set of simultaneous equations at discrete points, (d_i, l_j, t_k); i: 1 to m; j: 1 to n; k: 1 to p, in the data space. That is,

$$h(d_i, l_j) \blacklozenge g_1\{ x_A (d_i, l_j, t_k)\} = g_2\{ x_B (d_i, l_j, t_k)\} \qquad (4)$$

should be solved exhaustively. This is nothing but a problem in multidimensional interpolation. Invariance is possible using this method only if a unique solution to (4) exists, which depends on an appropriate choice of g_1. Designing an invariance transformation function in essence boils down to finding the most suitable g_1 for the data set given. As mentioned earlier, functions modeled by feedforward neural networks are ideal functional forms for g_1. In a practical application, images from two different camera location could be the two dissimilar signals that are required by this invariance transformation technique.

3. APPLICATION EXAMPLES

Two application examples are presented – one using experimental magnetic images of gas pipeline faults and the other using synthetic images that simulate the effects of variation in camera-object relative position. Each of these examples are described below.

3.1 Gas Pipeline Inspection

The natural gas industry plays a vital role in the economic well-being of the United States. Over 30% of the energy produced domestically is derived from natural gas; ensuring a safe and uninterrupted supply is extremely important. Today, natural gas is transported and distributed to consumers via a vast pipeline network that consists of over a million miles of pipe [6, 7]. About 280,000 miles of these are 24"-36" diameter pipes, which are usually buried underground. The pipeline system requires routine maintenance to continue safely and efficiently transporting this key energy supply.

The gas pipeline industry has developed procedures for in-line inspection of gas transmission pipelines starting in the early 60's. The latest inspection procedure employs a device known as a "pig" that is conveyed though the pipe under the pressure of natural gas (see Figure 2). The pig consists of a strong permanent magnet that magnetizes the pipe wall as it travels. When the magnet encounters surface-breaking defects on the pipe wall, a phenomenon called "magnetic flux leakage" occurs [8]. Some of the induced magnetic flux in the pipe "leaks" out of the pipe wall in the vicinity of the defect. This can be detected by flux sensitive devices on the pig. The pig also contains an on-board computer for digitizing and storing the flux leakage data. Such pipeline inspection devices can travel in the pipe for a few hundred miles; at the conclusion of the pigging operation, the stored data is retrieved and analyzed.

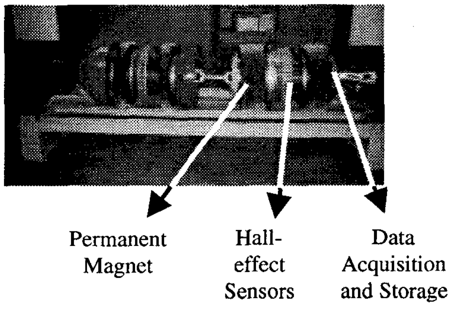

Figure 2. Gas pipeline inspection vehicle, the "Pig."

Magnetic flux leakage (MFL) signals are indicative of the location and geometry of the defect. This method of nondestructive testing (NDT) finds extensive applications, not only in the pipeline industry, but can be used wherever ferromagnetic materials are involved. There have been a variety of techniques developed for interpreting such signals in terms of defect geometry, starting from simple calibration methods [9] to artificial neural networks [10, 11].

A significant problem associated with interpreting MFL images is that the gray-levels of these magnetic images in regions containing pipe-wall defects vary depending both on the magnetization level in the pipe-wall and also on the depth of the defect. It is desired to suppress the former variation since very little knowledge or control exists for the magnetization level. On the other hand – image gray-level variation with respect to the defect depth must be retained – that is the whole point of the inspection process. The invariance transformation mechanism described in Section 2 is ideal for performing this operation. The algorithm requires two signals that are indicative of the defect geometry – these are obtained from the normal and tangential components of the leakage magnetic flux density vector (a 3-dimensional quantity). Figures 2 and 3 show input magnetic images from identical sections of pipe-walls with defects and output magnetic images from the invariance transformation algorithm respectively. Gray level variations due to changing magnetization level are reduced/eliminated whereas gray level variations due to defect geometry are preserved.

3.2 Camera-Object Relative Position

This portion of the study investigates the capability of the invariance transformation to compensate for the effects of classical image transformations that consist of image translation, rotation and scaling. In particular, the investigation focuses on the effects of image scaling that occurs as a result of unknown variations in the relative position of the camera and the object. For purposes of this initial a square object is chosen as the image template. The square object is imaged by placing a camera in two asymmetric positions about the center of the square – these generate two differing perspective views of the object, required for implementing the invariance transformation algorithm. The imaging geometry is shown in Figure 4. The purpose of this exercise is to determine if the invariance transformation algorithm is capable of characterizing the size of the square object, irrespective of the relative distance between the camera and the object.

Square objects generate trapeziodal shaped images, when imaged as described above. The effect of the relative positional shift can be described using the cross-ratio – which is defined as the ratio of the largest side of the image to its smallest. As the square object changes in size, and the distance of the camera varies, the cross-ratio does not remain constant for each square. This effect

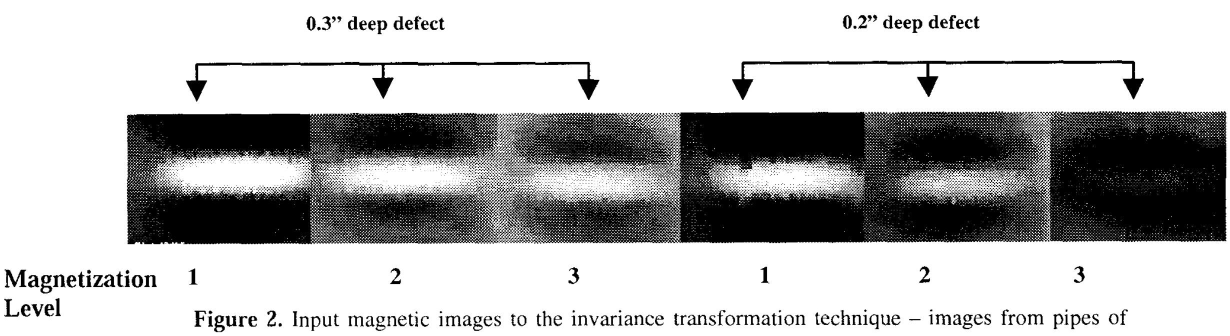

Figure 2. Input magnetic images to the invariance transformation technique – images from pipes of varying magnetization embedded with flaws of varying depth

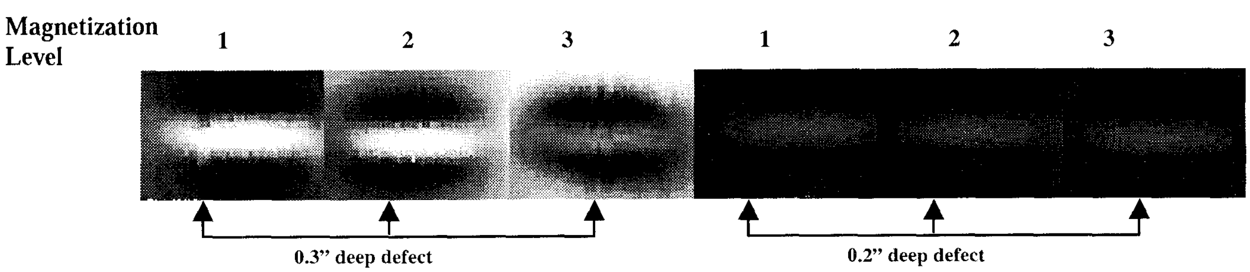

Figure 3. Output images from the invariance transformation technique – images from pipes of varying magnetization embedded with flaws of varying depth

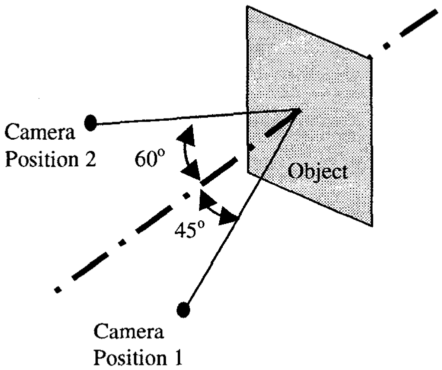

Figure 4. Imaging geometry.

is shown in Figure 6 which is obtained by simulating a set of square objects varying in dimension from 2x2 units to 14x14 units, when the camera is positioned is varied from {(3,3); (3,-3tan60°)} to {(10,10); (10,-10tan60°)}. However, after applying the invariance transformation algorithm described in Section 2, square objects of a given size will retain the transformed cross-ratio parameter, irrespective of the relative position from the camera. These results are also shown in Figure 6.

4. SUMMARY AND FUTURE WORK

As can be seen from the application examples, the invariance transformation algorithm described in this paper can not only compensate for the effects of classical image transformations, but also can be used to provide invariance with respect to operational parameters. Ongoing research in this area will consist of validating the technique using images suffering from the effects of simultaneous multiple transformations. Both synthetic and experimental images will be used for this study.

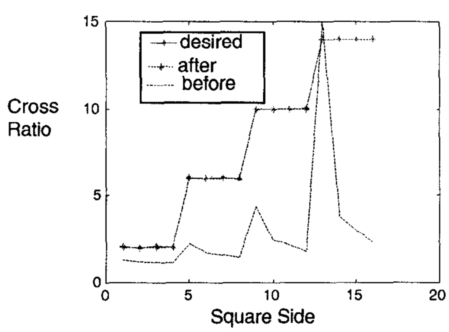

Figure 5. Cross-ratios before and after transformation.

5. ACKNOWLEDGEMENTS

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