Interpretation of Magnetic Sensing for Construction Inspection

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ABSRACT

The automatic determination of size and location of buried ferrous cylinders from magnetic observables are the focus of this work. Applications include mapping of reinforcement bars embedded in concrete and mapping of pipes buried in the ground. The problem requires an inverse solution to infer the attributes of an inclusion based upon observables which contrast the inclusion from its surroundings. Specifically, the inclusions of interest are ferrous cylinders, the observables are magnetic fields, and the surroundings are non-magnetic media. This inverse problem cannot be solved deterministically except for very idealized conditions. The subsystem methodologies developed here derive from the fields of sensing, image enhancement, object classification, knowledge representation, and inference capabilities. The system methodology is implemented to interpret ferrous cylinders from magnetic fields.

1 Magnetic Sensing and Sensors

The imaging and sizing of buried pipes in soil or steel rods in concrete are examples of the inclusion-in-continuum problem with the potential of wide utility in civil engineering. The accurate detection of embedded reinforcement is necessary to enforce the correct placement of reinforcement in new concrete construction. Accurate reinforcement detection including corrosion state is even more important in assessing the structural integrity of as-built or historical structures. Rebar detection is essential in operations such as coring and anchor emplacement in nuclear power plants.

A class of instruments have been specifically designed to meet the requirements of the manual inspection of reinforcement bars *in situ*. Their principle of operation falls in the category of the AC induction method, and a thorough examination of their observable characteristics has been made. The *covermeter* (Alternately profometer, pachometer, Fe-Depthmeter or R-meter [1]) is an electromagnetic device for determining the shallow cover to embedded steel, or is for locating the position of reinforcement and ferrous fittings in existing structures [6, 11].

Generally covermeters are used to determine either cover depth or bar size[1], while the other is known. However, there are occasions where both are unknown, e.g., in investigating an existing structure for which detailed structural drawings are not available. Peak reading alone is insufficient to determine both cover and bar size. This fact is illustrated in figure 1 where scans of two different bars peak at essentially the same intensity value. The figure reveals that a deeper, larger source creates a broader anomaly. The correlation of peak and cross-section properties enable determination of approximate depth to the source independent of any other information.

Although covermeters offer a great deal of portability and ease of use, in many instances even an expert operator is unable to identify patterns and to unscramble misleading measurements [13]. Covermeters typically perform well while used on lightly reinforced structural members. In heavily reinforced members the determination of cover thickness and individual bar size becomes almost impossible. Also bars that are positioned near the surface overwhelm deeper observations. Further, the density of manual observations is far too sparse to enable a complete imaging of reinforcing arrays. Only by automatically sensing and interpreting a large amount of data by magnetic imaging it is possible to reach higher levels of reliabilty in inspection.

[1]Reinforcement bars are manufactured in diameters from 3/8 to 2-1/4 in. and designated by the number of eighths inches contained in the bar diameter (e.g. 3/4-in-diameter bar is a #6)

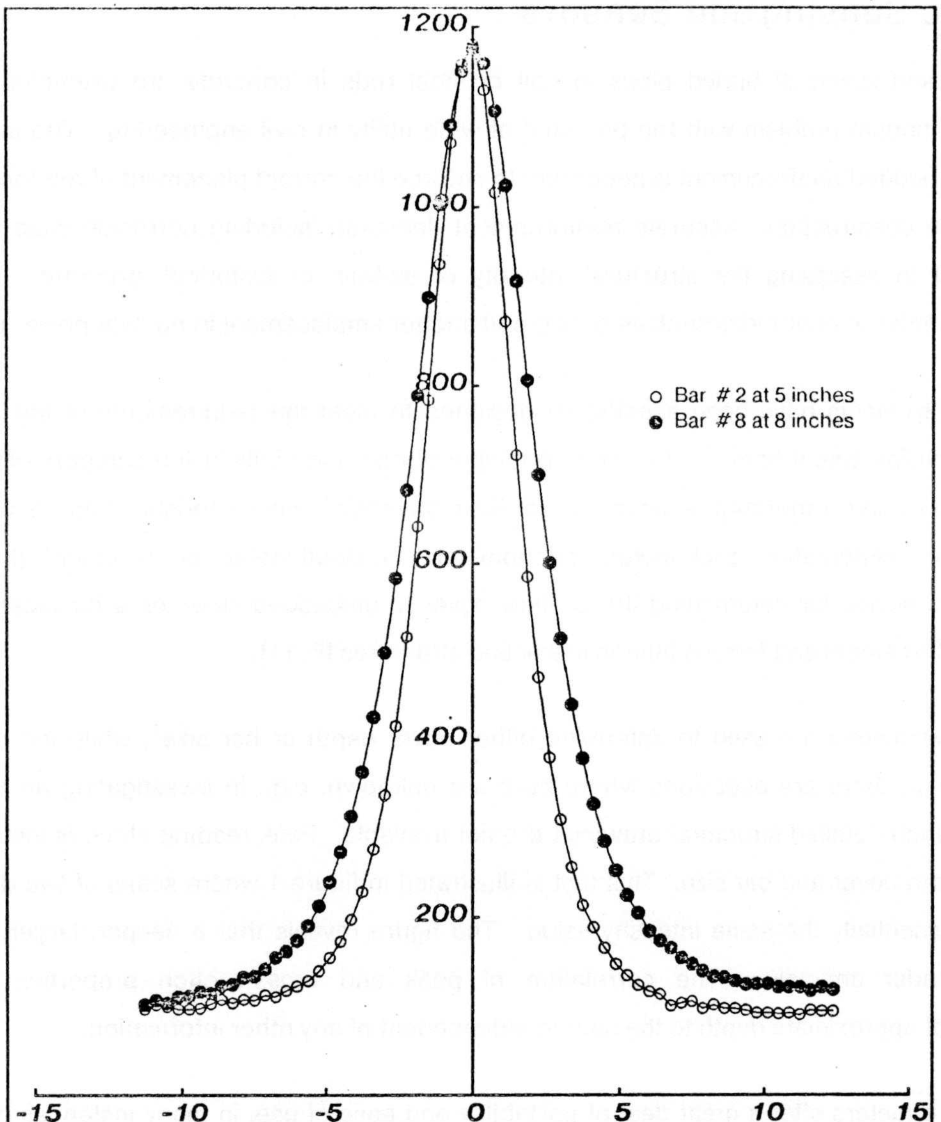

Figure 1: Peak aliasing of two different size bars

2 Problem Scope and Methodology

2.1 Problem of Inversion as a Mathematical Model

The "problem of inversion", is to obtain information concerning surface and subsurface conditions of a target object from a probe output signal. The measured signal is influenced by many interacting factors in the target object. Therefore the solution to the problem of inversion is possible only by the development of mathematical models that can predict these interactions. Magnetic modelling is complicated in two ways:

- The distribution of the magnetic field lines, even in a known material object, are not easily determined; and

- The inverse problem of imaging a source object from a surface magnetic field is known not to have a unique solution.

Despite these advances, not all magnetic field problems have fallen to numerical solutions. As a general rule, two-dimensional magnetic field problems, such as the non-linear two-dimensional Poisson equation or the two-dimensional eddy current and skin effect problems, may be considered solved. However, the solution of three-dimensional magnetic field problems by finite-element method is still problematic. Although solutions to these problems and improvements on the published procedures have appeared in the literature, FEM solutions require complicated problem modeling and lengthy solve execution time.

2.2 Why Magnetic Imaging?

Magnetic imaging solves the "inverse problem" of determining the dimensional properties of ferrous objects from the surrounding magnetic field intensities by representing field gradients as quantized images, and further employing tools in image processing to interpret the object features that constitute the image.

Signal processing and pattern recognition techniques have had successful implementations, making inferences in other than magnetic domains. Specifically, in medicine the automation of inspecting human anatomy has been seen in systems that use ultra sound, x-ray tomography or radiography [7] [2] [10]. In biological sciences the identification and classification of certain abnormalities in blood cells, chromosomes [5] [8] [10] and other bacterial entities have all been effectively automated by image processing. The literature is rich with references to applications of processing images obtained from aerial surveillance, astronomy, robot vision, circuit board inspection and many others.

2.3 Image Understanding Models

Image understanding is a descriptive process in which an image field is examined to generate some non-pictorial description of the image. A variety of models for image understanding systems have been proposed, however they all contain the same set of broadly defined processing and manipulating elements; feature extraction, symbolic representation and semantic interpretation. The models differ in their organization of elements, control flow among elements and the degree of inference employed in drawing meaningful conclusions [9].

Although the elements developed here for magnetic imaging stand on their individual merit, the crux of this work is the integration of magnetic vision system that infers and maps ferrous cylinders. The "bottom up" model of figure 2 represents both data and control flow of the implementation. The key to the success of this model is the reduction of information dimensionality from one stage to the next. This reduction is important, for processing complexity is greater at each subsequent stage of functionality. This approach is limited to applications where the description task is simple and the range of input imagery is narrow.

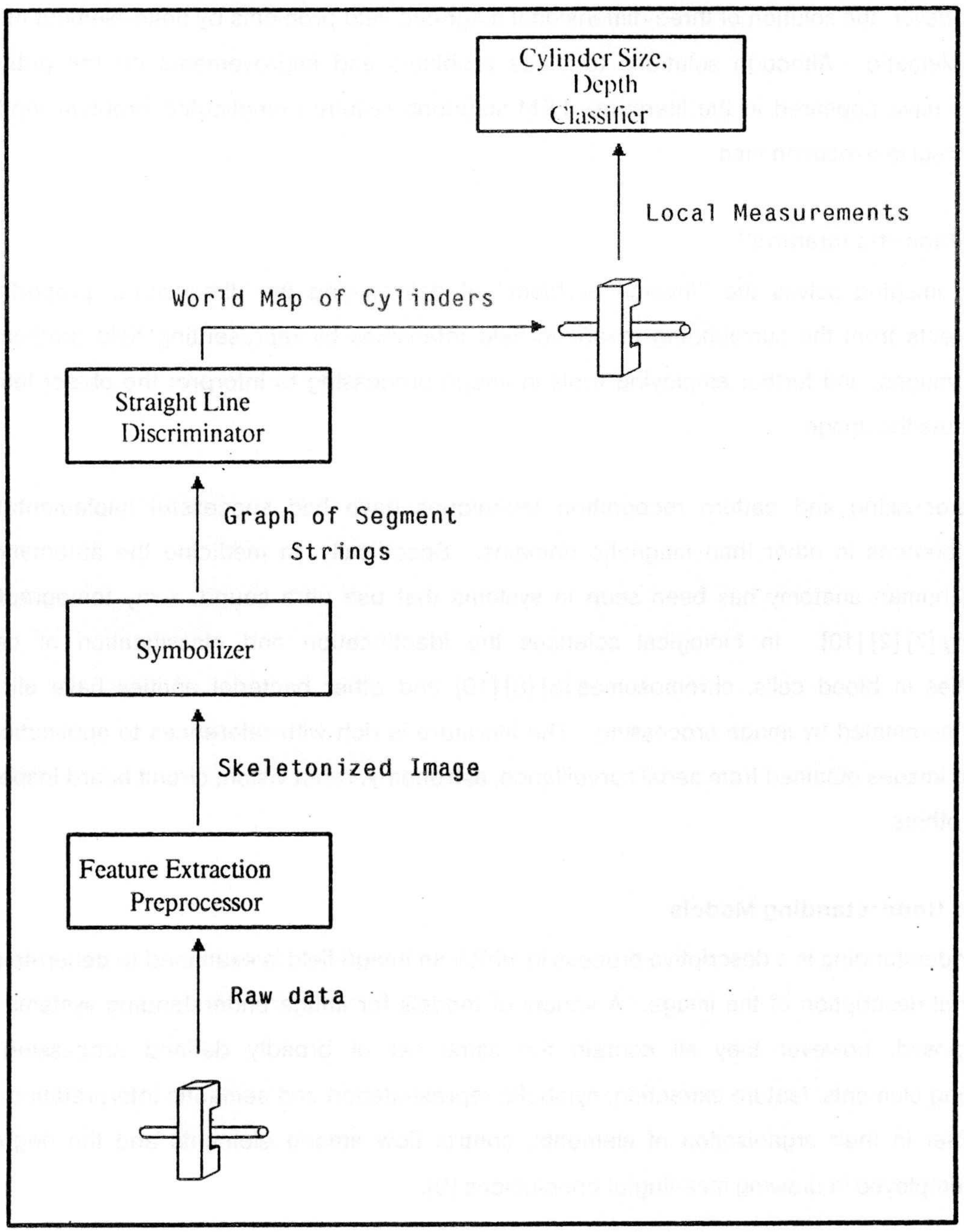

Figure 2: "Bottom up" approach of the experimental model

- Data acquisition is the most primitive task. Sensor readings are correlated to a spatial scan over the domain of interest. The data is grey-scaled in the manner of pixel digitization.

- Feature extraction preprocessing applies image enhancement, thresholding and skeletonizing operations to generate binarized chains of line-like features.

- Pixel chains are symbolized into strings of vertex coordinates which instantiate a graph of line segments.

- A cylinder axis algorithm performs simple assertions on segment chains (e.g. is a chain long? straight?) to infer admissible cylinder axis. The spatial relation among lines are investigated to classify patterns (e.g. intersection ? parallelism).

- At the highest level the system uses its hypothesis of cylinder topology to invoke emulations of human operator heuristic for determining cylinder size and depth. This takes the form of specifying actions to acquire additional data for use in correlations of cylinder depth and size.

This process hierarchy emulates somewhat the strategy of a human operator who searches intuitively to define a skeleton pattern. The search is directed by seeking magnetic features (e.g. peaks of anomalies) that correspond to pattern attributes. Using the knowledge of the pattern for directed search, the operator then correlates readings with known sensor signatures to infer target dimensions.

3 System Hardware

Figure 3 presents the implemented hardware configuration. The heart of the system is a Motorola 68000 based microprocessor board that is responsible for controlling the position of the robot arm, acquiring sensory data and performing various image processing algorithms on the generated images.

4 Image Decomposition and Object Classification

Figure 4 shows the magnetic image[2] of a single reinforcement bar. The image is shown in 16 levels of grey, and to a human observer the appropriate location and orientation of the bar is quite clear. However, the region surrounding the bar is very fuzzy, and it is difficult to precisely fix the locus of the bar.

[2] Throughout the remainder of this report a "Magnetic Image" is considered to be the grey scaled representation of a 2-D array of magnetic sensor intensity readings.

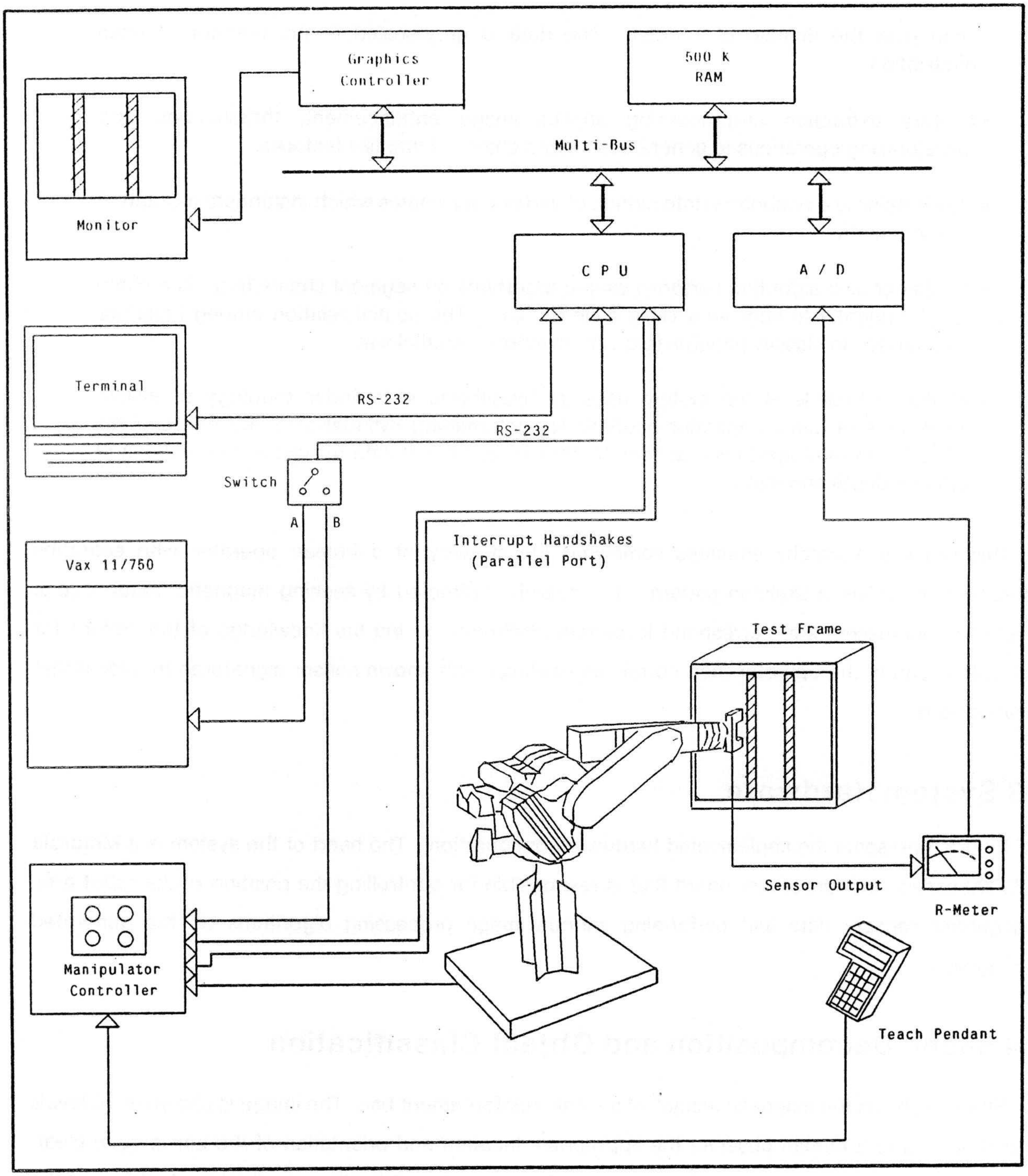

Figure 3: Hardware configuration

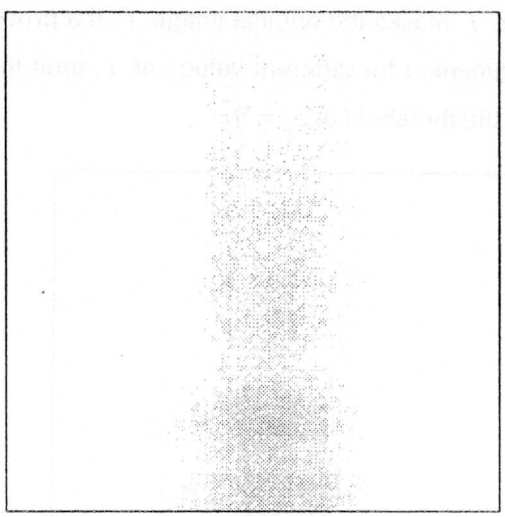

Figure 4: Grey scaled magnetic image of a single bar

5 Image Segmentation

5.1 Segmentation by Thresholding

Much work in pattern recognition treats scenes containing objects with fairly well-defined outlines (e.g., the recognition of machine parts in an automated workshop). In other applications (such as the classification of chromosomes in biological samples where the outlines are less sharp) the objects are distinguishable by applying a brightness thresholding operation. Magnetic imaging occupies the other extreme where the boundaries of objects are usually not well defined or are obscured by noise.

The edges of the magnetic image in figure 4 are highly diffused, however the segments of concern are the darkest region which represents the spine of the anomaly. Initial experiments were conducted on images that contained single cylinders, where it is adequate to segment those clusters of pixels that represent the peaks. For these cases there was no need to resort to algorithms that recover diffused edges, and simple brightness thresholding produced satisfactory results.

The most common means to extract objects from an image is to *Threshold* the image. A function $f(x,y)$ represents the greyness intensity in the range $[z_i, z_K]$ of an image at coordinates x and y of the image. Given an image f, and t, which is any number between z_i and z_K, the result of thresholding f is the two-valued image f_t defined by:

$$f_t(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geq t \\ 0 & \text{if } f(x,y) < t \end{cases}$$

The resultant binary overlay image f_t' masks the original image, f. If a property about f_t' is known in advance, the image f can be segmented for different values of t, until the desired f_t is obtained. Figure 5 is the image in figure 4 at the threshold of $z_k = 9$.

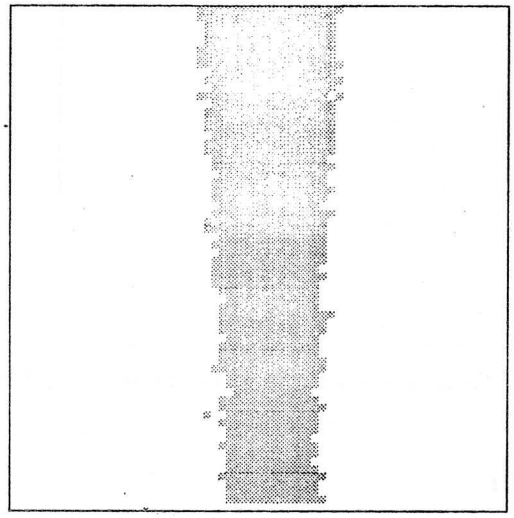

Figure 5: Binarized image of fig.4, $z_k = 9$

5.2 Skeletonizing

A skeleton or stick figure representation of an object is often sufficient to express the structural relationship of complex objects in a scene [9]. In this work a connected chain of pixels that coincides with the main axis of a segment in a magnetic image is a clearer representation of a ferrous cylinder than the raw data. The idealized thin line not only satisfies the requirement of defining the topology of buried elements, but also satisfies, the definition of a line as "that which has length without breadth" while still retaining its connectivity. Skeletonizing is best defined by the "prairie fire" analogy [3] where a shape to be composed of dry grass and the boundary of it to be the source of a fire or wavefront. If the fire were to start simultaneously on the perimeter of the grass, the fire would proceed to burn toward the center of the shape until all of the grass was consumed. The points at which wavefronts first meet form a "skeleton" or quench lines, which are the locus of points that are equally distant from at least two closest points on the shape boundary. Each point has a function assigned to it which is the value of its distance from the edge[3]. This transformation is reversible, in the sense that the original object may be obtained by the isotropic expansion of the skeleton a number of times equal to the maximum value of their distance from the closest edge. The pruning of the skeleton also allows for smoothing the original object during reconstruction. Figure 6 is the resultant skeleton of the segmented image of figure 5.

[3]This is the "quench function" of Blum

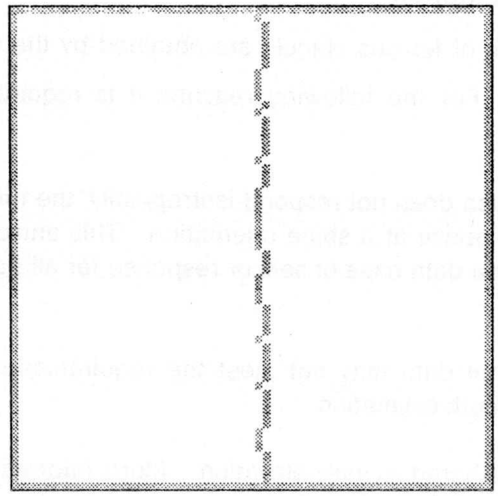

Figure 6: The stick figure representation after skeletonizing figure5

5.3 Symbolizer

Once parts of a magnetic images can be isolated as meaningful line segment entities that define a topology *figure*, the next objective is to define these line segments in terms of their geometric properties.

In describing the lines or line like figures, two problems need to be overcome; where to break the original figure into segments, and how to fit a line to each segment [4].

The one pixel wide skeletons that are representations for ferrous cylinders are a collection of pixels in the image that exhibit no association with each other. The line segment extraction scheme outputs from the image a symbolic image, with a data structure representing the relationship of groups of pixels that define individual line segments (contours). This data structure is a record structure containing the following information [12]; Starting point x_0, y_0 of each (line) in the image, ending point of the line, a flag indicating whether the contour is closed or open, the array of bidirectional pixel coordinates making each line and the arc length of the contour.

6 Size / Depth Heuristics

Once the pattern of individual steel rod segments have been determined, the manipulator performs local post sensory measurements near the midpoint of a segment. The mid-section as a rule of thumb is an area where the non-uniform bar end response has the least impact. In multi bar problems where bars can cross one another, each crossed bar is segmented into segments, and the mid-section of each segment offers the quietest region for making additional measurements.

6.1 Cylinder Size and Depth Estimation

The size and depth of placement of ferrous objects are obtained by the correlation methods and sensor response characteristics. For the following reasons it is required that a rescan by the manipulator be performed.

1. For the case of a sensor which does not respond isotropically, the original raw data is a representation of sensor response at a some orientation. This anisotropy expands the solution space, and requires a data base of sensor response for all possible orientations of objects and sensor.

2. The resolution of the original data may not meet the requirements of the estimating techniques of bar size and depth estimation.

3. The initial information is gathered at one elevation. More information is available at different elevations (e.g. for "shimming").

7 Conclusion

The application of higher technologies to Civil Engineering tasks in construction and inspection is more tractable now than ever before due to the advent of accurate robotic manipulators, artificial intelligence, smart sensor technology, and faster and less expensive computing power. Unlike most settings, where these technologies are implemented in highly predictable environments, in construction, the work space is dynamic and the unexpected is the norm. As a result, task execution and passive awareness of changing environments are dependent on sensory perceptions and intelligent software. Contributions to, and applications of the state of the art in sensory systems and their utility is imperative in strategizing task execution in the construction setting.

The objective of this work has been to explore the integration of a class of sensory devices into a system that can reveal spatial information that is pertinent to the domain under study. Unlike natural scene pictures, magnetic images are artificial scenes of fields which are only indirect information linked to target objects. Although a priori knowledge of the expected target shapes is available, the exact scene content is unknown a priori.

Unlike a human operator who is blind to the complete picture of anomaly behavior, the automatic thresholding and skeletonizing tasks are global and prove to be effective in delineating all features that are common to target anomalies. The liabilities of the human "search and see" sequence are circumvented. However, the algorithm performs well only for those cases where ferrous elements are sparsely placed.

The outcome of this project is useful to task control applications where it is necessary to remove the media around each object without harming the inclusion. The skeleton of objects can indicate the areas to be avoided. Applications include locating and excavating utility lines in the ground, and drilling concrete walls without harming the reinforcement.

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