# final report

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# An overview of medical technology, with possible applications within the meat processing industry

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# Contents

# 1 Introduction

It is highly desirable to automate the meat industry; factors include increased hygiene, speed, safety for employees and reduction in labour costs. The main complication in automating the meat industry is the high level of variability between products. This requires each specimen to be analysed individually and a unique solution obtained for each carcase. The process can be broken up into the following process.

1. Collecting data from the carcase.
2. Segmentation of carcase components
3. Analyse the segmented data and map out an appropriate cutting path

These three steps can be analogous to a modern medical diagnosis of some ailments, where part three is the diagnosis and treatment made by the doctor. The most developed internal imaging technology for biological beings has been developed for the medical industry. Segmentation of various components of the human body such as grey and white matter for brain scans, internal organs, bones for body scans and separation of pectoral muscle from breast tissue when scanning for breast cancer, have also been developed to aid doctors in making a diagnoses. This report covers some medical imaging techniques used to image humans, automated data processes, as well as a brief description of new medical cutting processes and robotics within the medical industry.

# 2 Imaging

Commercial visioning systems that are used in the medical industry include ultrasound, Xray imaging, Duel Energy Xray Absobiometry, (DEXA/DXA) Computed Topography, (CT) Magnetic Resonance Imaging, (MRI) as well as other modalities that use radioactive traces to enhance images, (imaging modalities that use radioactive traces have not been investigated for this report, due to the accumulative effect of radioactive materials). Other technologies that are still under development include Microwave Imaging, (MI) Microwave Tomography, (MT) PhotoAcoustic Tomography, (PAT) and ThermoAcoustic Tomography, (TAT).

The other part of medical imaging is segmentation, this is primarily done for three dimensional imaging and aids in allowing the data to be presented in a meaningful way. For example, allowing various organs and parts of organs to be viewed individually. There is also a lot of interest in the automation of locating tumours in various parts of the body.
Challenges in this process include high Signal to Noise Ratios, (SNR) with various levels depending on the imaging modality, high variability in general and the alignment of scans. There has been a range of different approaches to this problem including fuzzy logic, intelligent mesh refinement, statistical methods, deformable models, neural networks and hybrid schemes.

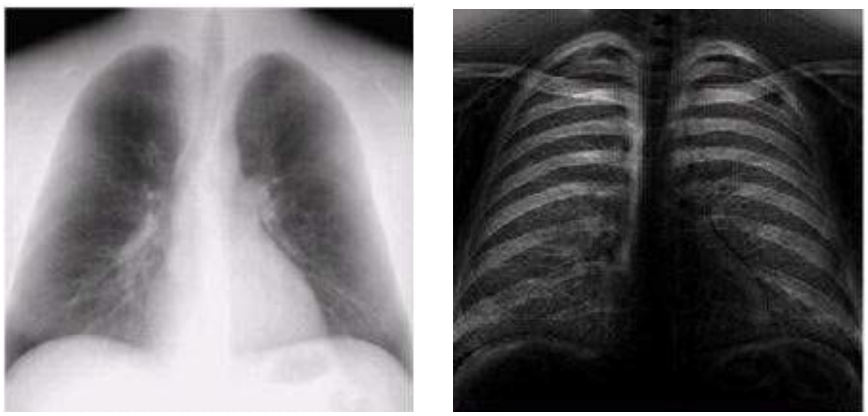
## 2.1 XRay Based Imaging

Xray imaging is the oldest of all medical imaging modalities. Generally Xray imaging refers to projection Xray imaging in which the attenuation of Xrays shot through a body is measured. An image is formed due to higher density materials attenuate the Xray signal to a larger degree. Standard Xrays are generally used to view the condition of bones and to check for chest infections. Xrays can be measured by a radiograph, (Xray photograph) fluoroscope or digitally.
A major limitation with radiography is that the area being Xrayed needs to be relatively uniform in thickness to avoid over exposing parts of the image and under exposing the rest.

DEXA is another form of Xray imaging; it is primarily used in the medical industry to measure the bone density; however it can be used to measure fat/muscle content. DEXA products create images by scanning the body with a fan beam. This technique could also allow a lean/fat ratio distribution along the length of a body.

Figure[1] gives an example of a high and low energy DEXA images.

These images were used in[1] to train an artificial neural network to suppress the ribs with a plain chest radiograph. DEXA separates hard and soft tissue by using two measurements; the first is a low energy Xray and the other is a high energy Xray. Only hard tissue is visible on the high energy Xray. This is subtracted from the low energy Xray leaving only the soft material.



**Figure[1], (left), soft tissue DXA chest radiograph, (right) hard tissue DXA chest radiograph**

CT scanners use Xray imaging to produce three dimensional images by taking projection images from multiple angles and then the image is reconstructed for a thin slice. Three dimensional images are formed by putting the slices together.

The internal CT image for a slice is created by breaking the internal volume up into voxels, (volumetric pixel) and enough images need to be taken to from as many unique equations as there is voxels. So for a standard 512x512 image, approximately 262144 images need to be taken per slice to prevent aliasing. CT scanning has become a fast three dimensional imaging tool mainly due to the development of conebeams, electron beams and multislice scanners. Cone beams have speed up the process by scanning larger volumes rather than thin slices, multislice scanners simultaneously scan and can continue scanning in a helical motion. Electron beam CT scanners have eliminated all mechanical movement, allowing a single slice to be taken in as little as 25ms. Philips Brilliance CT scanners permit whole body imaging for diagnosis in less than 50 seconds, (0.5mm thin slices)[2]. Figure[2] shows a whole body scan after post processing.

Other commercial CT products include the Seimans multislice scanner, (up to 64 slices per rotation in 0.37 sec) and GEs electron beam CT scanner that is capable of scanning at 50ms per slice[2].

Figure [2], full body scan by a Philips Brilliance CT scanner. (An image enhancing agent was injected to give the internal organs a higher contrast)

Magnetic Resonance Imaging Nuclear Magnetic Resonance, (NMR) is the phenomenon used in Magnetic Resonance Imaging, (MRI). When the body is passed through a large magnetic field and excited by a Radio Frequency, (RF) pulse, some protons, (mainly hydrogen) are excited and spin at the lamor frequency. When the magnetic field is turned off the spinning protons relax and emit there own RF at this frequency.

The frequency the protons emit is proportional to the frequency of the magnetic field. Different material properties can be identified by the signal strength or the signal decay time. MR images are then obtained by encoding the response frequency in space by applying gradients in the magnetic field. The resulting signal is measured and is converted into its Fourier space. The magnitude of the signal for each frequency corresponds to a spatial location. The magnetic field is then shifted to scan along another line. MRI is the most expensive of the well developed imaging modalities, but the image quality is high and it is termed nonevasive and safe because it does not emit iodizing radiation. Since its introduction, MRI has some what replaced many applications of the CT scan due to it being termed noninvasive.

MRI is somewhat slower producing three dimensional images than CT scans and the large magnetic field reduces the use of metallic objects and electric motors near the MR machine. MRI maps out the water concentrations throughout the body by obtaining a signal from hydrogen protons. The majority of hydrogen atoms in the human body are from water molecules. Due to the signal being generated internally, voxel widths need to be somewhat thicker than CT scans to be able to maintain signal strength. In both CT and MRI scans, image enhancers are often injected into the patient. This would not be possible to do in a meat processing environment.

## 2.2 Ultrasound

Ultrasound imaging is the most widely used imaging modality next to standard projection Xraying. It is also the cheapest and most portable of imaging modalities commercially used. Ultrasound imaging is capable of producing higher resolution images than both CT and MRI, however ultrasound imaging has a maximum depth range of about 2540cm and only a small area is completely focused at one time.

Both the depth of penetration and the image resolution are highly dependent on the frequency used and it is often a trade off between the two. The biggest advantage of ultrasound imaging is it's capability of producing “real time” images and can be used to measure motion such as heart valves and even blood flow, by detecting the frequency shift due to the Doppler effect. A problem that occurs with ultrasound scanning with regard to image quality is the SNR, (a large amount of noise/”speckle” is often picked up). Much of the research in this area involves filtering out the noise and using various algorithms to reconstruct and segment various components of the area/volume of interest.

The most simple of ultrasound probes consists of a single piezoelectric element for both sending and receiving the signal, acoustic backing to damp out the element vibrations before receiving the reflected signal and an acoustic lens for steering the signal. These probes are required to be swept along the surface of the volume being scanned. In early the days, this was done manually but is now done by mechanically moving an acoustic lens to focus on a particular point. Other ultrasound scans use an array of elements which enable an image to be formed instantly, (an alternative to scanning in one direction with a single element probe) or time delays can be applied to each element creating an acoustic beam controlled electrically allowing dynamic focusing. In 1997 real time volumetric imaging became commercially available using 2D phased arrays [3]. Currently there is a lot of research being undertaken in the processing of 3D ultrasound images. The amount of information that needs to be processed has become somewhat of a challenge to produce real time 3D images that are meaningful to the viewer.

## 2.3 New Imaging Modalities

New imaging technologies still under development include MI, MT, PAT and TAT. Most of the research for microwave based imaging in the medical industry revolves around detection of breast tumours. Current detection methods include Xray, (mammogram) or ultrasound. Both of these methods detect density changes, making it hard for tumours to be detected in dense breasts.

However the dielectric properties of breast tissue and tumours/cysts have a significant difference, giving microwave imaging an advantage in image contrast over both ultrasound and Xray based techniques for imaging soft tissue. A much lower signal to noise ratio is also achievable with microwave based imaging. Tables[1] highlights the variability of dielectric properties in human tissue at 2.5GHz. It is almost a certainty that the detection and location of breast cancers will be among the first commercial medical applications of microwave based imaging [4]. The other motivation for the development of microwave based imaging is that it does not emit any iodising radiation.

## 2.4 Microwave Imaging (Radiometry)

MI uses a passive microwave radiometer to measure the microwave radiation naturally emitted by a body similar to inferred photography. This method has the potential to give an insight into the physical state of a carcase up to a certain depth which may be useful for locating rib interfaces, or external fat depth. Research has mainly been centred on detecting breast cancers in the medical industry. Although an investigation into the use of foreign body detection in pre and post operative care has been investigated[5].

| Tissue | $\epsilon'$ | $\sigma(S/m)$ |
|---|---|---|
| Blood | 56 - 60 | 2.5 |
| Bone | 12 | 0.4 |
| Brain (Grey matter) | 45 | 2 |
| Fat (Not infiltrated) | 4 - 5 | 0.07 - 0.1 |
| Heart | 55 | 2.3 |
| Kidney (Cortex) | 55 | 2.5 |
| Liver | 42 | 1.8 |
| Lung (Inflated) | 20 | 0.7 - 0.8 |
| Muscle | 50 - 55 | 1.8 - 2.2 |
| Skin (Dry) | 38 | 1.5 |
| Skin (Wet) | 43 | 1.8 |
| Spleen | 52 | 2.2 |
| Tendon | 42 | 1.8 |

**Table[1], approximate dielectric properties of human tissue at 2.5GHz.**

## 2.5 Microwave Tomography

In MT data acquisition is quick, although the solution of the Maxwell equations are needed to reconstruct the image, this can be rather time consuming due to the highly nonlinear properties of the governing equations and the discontinuous nature of biological tissues.
The main advantage of MT is that the dielectric properties are measured, (which are dependant on the physiological state of the tissue) this gives the images a high level of contrast between soft tissues that is not possible with density based measurements, (Ultrasound and Xray).
It has even been suggested[6] that it is possible to possible to differentiate between healthy and leukaemic bone marrow through MT. Figure [3] shows a 2D mesh for MT, the antennas measure the boundary conditions and excite the body being imaged. The governing equations are then solved for the internal mesh points.

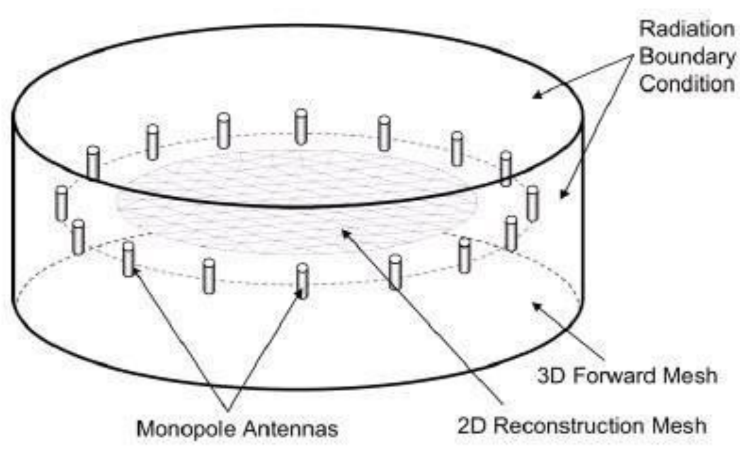



**Figure [3], schematic set up for microwave tomography**

## 2.6 PAT/TAT

PAT and TAT use laser and microwave pulses respectively, to cause a thermoacoustic wave in the tissue that is detected by a piezoelectric material in the same way as ultrasound. These technologies provide a higher level of contrast between soft tissues than ultrasound due to the acoustic wave intensity being dependant on physiological properties of the tissue, (rather than the acoustic impedance), while still retaining the higher resolution of ultrasound. PAT/TAT is capable of producing high quality three dimensional images in real time.

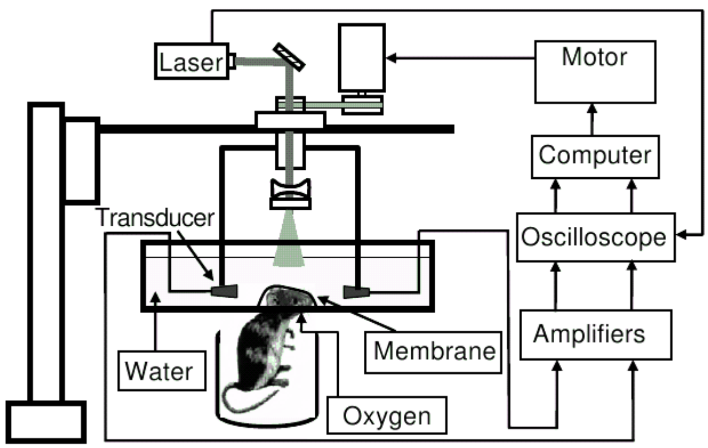



**Figure [4], experimental set up for in vivo PhotoAcoustic Tomography on a rat brain**

As with most microwave based imaging techniques the detection an location of tumours is of high interest for researchers in this field, although locating foreign bodies in surgery has also been investigated[5]. Figure[4] shows an experimental set up for a live rat for detection of brain tumours. PAT/TAT is a fast high quality imaging modality that is safe and does not emit any iodising radiation.

### 2.7 Comments medical imaging

Among the medical imaging procedures, Xray based imaging is probably the most appropriate, (digital, DXA and CT) to be applied examine carcases in a processing environment. It is fairly quick, (compared to other imaging modalities) and can provide detailed information about bone structure and soft tissue. The cheapest of all modalities is ultrasound; however the ultrasound probe needs to be in contact with the object, a gel is generally used to eliminate any air pockets between the skin and transducer. A low speed water jet can be used as a medium[7] but this somewhat reduces the amount of information that can be acquired. PAT and TAT may have similar restrictions, although the transfer of the acoustic signal through the large change in acoustic impedance will only occur once. MRI is the most expensive commercially used imaging modality, however it has been investigated for use in the pork industry to monitor the diffusion of sodium ions, (curing process) for ham[8].

# 3 Intelligent systems

Due to the high variability of biological beings, not all data points can be obtained, often leaving an ill defined problem. Analytical models can be difficult to create and implement. Implementation of such models, often require gross approximations. One way around this, is to create intelligent systems. The main forms of intelligent systems include fuzzy logic, artificial neural networks and evolutionary algorithms. What defines an intelligent system is its ability to learn. There are a range of training techniques available. The most common of training methods is supervised learning. This requires large amounts of information regarding the system inputs and desired outputs. The system is then trained to mimic the desired outputs. This method requires careful selection of the training data and sometimes the training data is filtered to stop the system from trying to approximate noise. The other class of training is unsupervised training. Two examples of unsupervised training are positive reinforcement and competitive learning. Unsupervised training methods are not always reliable and can sometimes deviate from a stable solution.

Implementations of intelligent systems are extremely flexible. Some implementations include competitive systems where the systems compete against each other. Others include and fuzzy knowledge based systems over viewing neural networks being optimised by genetic algorithms. Most intelligent systems are computer based but fuzzy controllers are wildly available and ANN can be produced as a chip. The first ANN to be produced as a chip was to validate signatures for American banks.

These types of systems have acquired a lot of interest for applications within the medical industry, mainly due to the high level of variability and uncertainty within biological beings. Some examples include image segmentation, anaesthesia control, Computer Aided Diagnosis, (CAD) automated tumour detection and even adaptive control for artificial limbs.

### 3.1 Fuzzy logic

Fuzzy logic is highly useful due to it being able to recognize approximate instructions in linguistic format and being able to process the data in a methodical way. The idea of fuzzy modelling came from the fact that the world is too complicated for a “crisp” model to predict real processes. Fuzzy decision making tries to mimic the human thought process by coupling recognition with a degree of certainty. Fuzzy modelling relies on data sets that are “fuzzyfied” which are used to describe the process. “fuzzyfied” data is grouped into classes and defined by a weighted membership

value. Classes overlap and the data can be a member of more than one class. An example of triangular membership functions for a variable is shown figure[5]. Other common membership functions are trapezoidal and Gaussian distributions. The weighted membership value can be thought of as a certainty factor. The Main motivation behind fuzzy systems is the ability to process human ideas in the form of weighted membership values for a variable, such as part of a biological being can be hard or soft or rib A is near rib B.
Such instructions are easily dealt with fuzzy logic and are then processed with If-then statements, effectively passing the data through a filter to obtain precise outputs using fuzzy rules.

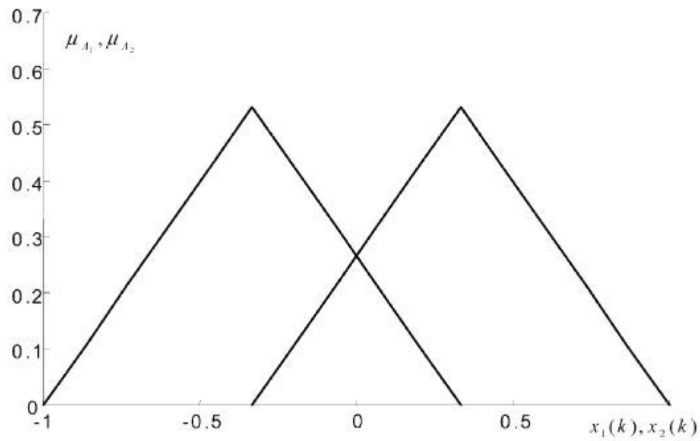



**Figure [5] triangular fuzzy membership functions with two classes representing a particular variable.**

Since fuzzy data can be defined in a linguistic sense, definitions can also take advantage of expert knowledge and process fuzzy data based on expert rules so that a system can mimic an expert.
Fuzzy membership functions can also be adapted to optimize the output of the system, while still applying the same expert based rules.
Fuzzy-c means is a common unsupervised training algorithm for fuzzy sets. This method is often used in image segmentation. The membership functions are optimised to produce the highest level of certainty. This optimisation problem is usually performed using lagrangian multipliers, but evolutionary algorithms or artificial neural networks have been used. The pixels/voxels that then have the minimum membership values are treated as the interface between two or more objects. This can also be used to compress an image into a centroid and a surface for each component greatly reducing the amount of memory needed to store the image as well as supplying the data in a more meaningful format that is simpler to process. Fuzzy-c means algorithms have constantly been reported to be more accurate than hard clustering methods such as K-means and hard c-means algorithms[914].

Once the fuzzy membership functions are optimised they can also be used to process the data further incorporating other fuzzy data sets.

## 3.2 Artificial Neural Networks

ANN are made up of inter connected neurons in various configurations and the neurons pass weighted signals to each other. A simple artificial neuron is shown in figure[6], illustrating the output signal is dependant on the sum of the weighted input signals. A basic network is shown in figure[7], it can be seen that even a basic network is very flexible in the way it can operate due to

the number of modes possible. ANN are trained to perform a specific function by using optimisation algorithms to minimise the output error by adjusting the weighed values of various signals passed to other neurons.
Dynamic neural networks can also delete neurons if they don't seem to have any contribution to the network and add neurons if the system needs to be more complex. ANN are very good a being able to find complex patterns among noisy signals and approximating highly nonlinear systems. These two factors make ANN good candidates for recognition, and system control.

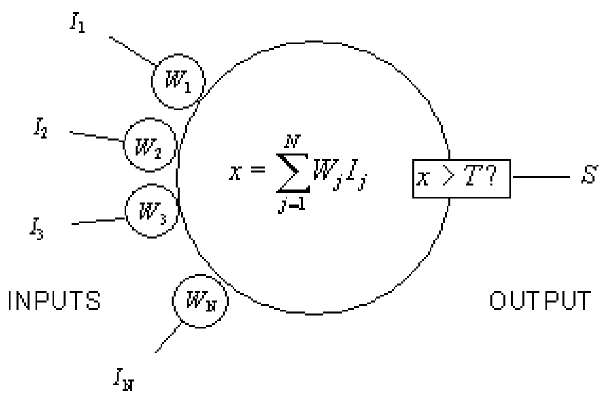



**Figure [6], simple artificial neuron**

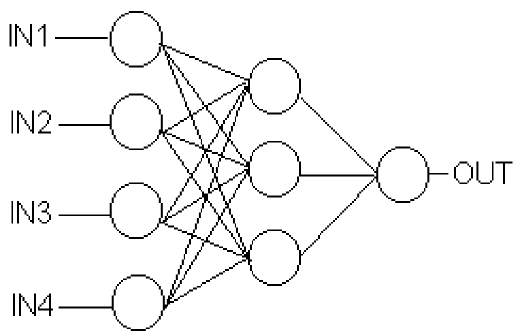
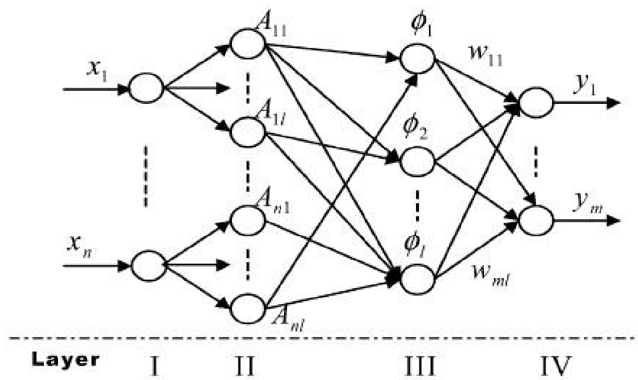



**Figure [7], simple feed forward peceptron ANN**

ANN are naturally parallel making them well suited to parallel computing, however they are generally computed in a serial fashion which greatly reduces their computational potential[15]. ANN have had good success in image segmentation, automated detection and classification of nodules and suppression of ribs in chest radiographies, (making it easier to find nodules in the lung).

## 3.3 Fuzzy Neural Networks

Fuzzy neural networks use fuzzy input data for an ANN. The ANN acts as the decision control in the absence of expert knowledge. The fuzzy membership functions are usually also allowed to be optimised during the learning phase.
Fuzzy ANN have been found to learn more quickly than plain ANN and are more tolerant to noisy data due to the filtering effect of the membership functions. Figure[8] shows a general fuzzy neural architecture, layer 1 receives the input variables, layer 2 sends a signal based on the fuzzy membership weights, layer 3 is the input for the main ANN, layer 4 is the output layer in the ANN.




**Figure[8], Fuzzy Neural Network architecture.**

## 3.4 Evolutionary Algorithms

Evolutionary Algorithms, (EA) are a class of optimisation algorithms that use the process of evolution to reach an optimum or near optimum solution. EA are generally better at finding solutions in highly nonlinear problems and get stuck in local minima less frequently than most other optimisation algorithms. The other advantage that EA have, is that they do not rely on gradients to reach a minima, making them more tolerant to noise. Genetic Algorithms, (GA) are a common class of EA. GA use populations with different genetic codes. These populations are then performance tested against a fitness function. The best performing individuals are then mated up and produce offspring. Often a low probability of genetic mutation is added into the algorithm. This helps the solution avoid being stuck in a local minimum. There are a large range of methods to decide the level of mutation such as which individuals should mate, which ones are killed and which individuals or groups decide the best approximation. These decisions are the core of designing GA.
EA have been applied to a range of optimisation problems including curve fitting, training fuzzy relations, and optimising ANN. The latter is fairly interesting because some approaches use ANN as a fitness function in population control, (effectively training the EA).

All types of intelligent systems have had good success in image recognition, clustering and approximating nonlinear systems. These intelligent systems are extremely flexible and generally can process data more quickly then complex models, once the system is trained[15]. The concepts of intelligent systems are relatively simple, although the system design and training of these systems is not trivial. The core of these systems is the optimisation process during training, and the selection of inputs as well as training data. These factors are of vital importance in the design of a successful intelligent system.

## 3.5 Robotics

Currently the main use for robots in surgery is smoothing the hand actions of the surgeon and to operate internally while causing as little damage to other areas of the body, (eg. key hole surgery), enabling a faster patient recovery time.

Orthopaedic surgery is a good example of where medical robots have been applied. The cutting/preparation of bone to high tolerances is of great importance for many orthopaedic applications making it an ideal area to develop robotic devices for machining. Other areas include laparoscopy, microsurgery and Image Guided Surgery, (IGS). The main advantages are the transfer of exaggerated forces experienced by the robot to the surgeon, smoothing out the motion from the doctor to the robot and ensuring all utensils remain in a save volume of space.

Among surgeons, there is a mixed opinion regarding medical robots. Most agree that the surgery time is increased and the cost is offset by the increased patient recovery time.
Image Guided Surgery, (IGS) is a procedure in which the surgeon is able to get updated internal information about the patient throughout the surgery. Xrays are generally taken and a fluoroscope is used to produce real time images, ultrasound scans are sometimes used. The main application of using this technique is to be able to avoid moving instruments into a dangerous position; this may occur during brain, or back surgery. IGS is a major part of surgical robots to provide the surgeon with additional information that can not be obtained by the human eye. Commercial products that enable IGS are the Carm and the more recent addition, the Oarm ™; they are both portable Xray machines that allow images to be reproduced in real time from a large range of angles while overcoming the problems associated with space restriction, allowing plenty of room for the surgeon to move.

The Oarm ™ is also capable of producing three dimensional images in the same way as a CT scan; however a full scan of a particular crosssection takes around 13 seconds. Mechanically the Carm is capable of this but due to its physical design, high quality images are challenging to achieve. Currently researches are trying to develop the Carm making it capable of CT scans [16]. The current manufactures of the Carm include Philips, Siemens, FluroScan, XiScan, General Electric among others. The Oarm ™ is produced by Breakaway Imaging. MRI requires more research for this application. The large magnetic field produced by the MR scanner restricts the use of metallic objects near the MRI system.

One problem encountered in IGS, is the actual image location relative to the patient, one solution that has been investigated is focussing a digital camera on a particular maker points on the patient and correlating the internal image relative to the position of the digital camera[16].
The other approach to IGS is the use of preoperative images, via CT or MRI scans. When dynamic organs are involved, (heart, lungs and various arteries) deformable models have been considered[1718].
These models include complex physics and the time taken to solve these equations, is somewhat infeasible within the operating room. For a smaller expense the dynamic behaviour of organs can be viewed in real time using an ultrasound scan.

Robots in the medical industry are applied to a variety of surgical procedures. For it to progress further, image processing software needs further development. Automation of any surgical robots is a long way off; even in orthopaedic surgery, where high machining tolerances are desired, surgical robots are still controlled by a joystick while machining, allowing the surgeon to always be in full control. New Cutting Tools Apart from the scalpel, tools used inside a surgical room do not differ very much to the cutting tools you would find in a typical workshop, saws, chisels, grinding stones and drills are used primarily to penetrate or remove bone. Some investigations have included abrasive water jets [1920] and laserwater jets [2223] for osteopedic surgery, where both of these technologies are already established in many engineering industries. Plain water jets that have been developed commercially for medical applications. These include, versajet, (a high powered parallel water jet) used for wound debreiment[21] and spinojet used to remove soft tissue during spinal surgery.
The benefits of using water jets include, low mechanical forces, high level of hygiene, no induced vibrations and low thermal stress. These factors are highly desirable and allow a decreased patient recovery time.

The investigations for oestipedic procedures using abrasive water jets used a type of salt[20] and lactose[19] for the abrasive. Tests were carried out to investigate the cutting performance[19] and quality[20] for both bone and bone cement. The pressures used were extremely low in both investigations, as increased safety was desired for the patient. The surface quality was found to be high enough for various osteopedic procedures. It has been suggested that abrasive water jets could be a feasible option for osteopedic surgery if the jet can be further optimised[19].

There have been various studies investigating heat generation in bone due to laser ablation[2224]. Energy from the light is absorbed, (mainly by water) causing rapid heating of the material resulting in ablation. When conditions are favourable, the process becomes rapid enough to have minimal heat transfer to surrounding material. Temperature increases 2mm away from the cut were measured and found to be less than when conventional methods were used[23], (saws, drills, ect). Closer temperature measurements could not be obtained without directly exposing the thermometer to the laser. The role of the water jet in bone ablation is to increase the laser absorption in the bone, remove debris caused by the laser and assist in cooling.

The high powered parallel water jet developed for wound debridement uses a high pressure water jet that is directed horizontally across the contaminated wound, debris is then sucked out due to the venturi effect. This new method is used to remove foreign matter and undesirable tissue, (infected tissue) while preserving the maximum amount of healthy tissue. It was found that the people who underwent this kind of procedure require much less treatment than those who wounds were cleaned via surgery. It was estimated that this device could lead to a saving in around $1,900 per patient that is suitable for this kind of treatment.

# 4 Discussion

Mentioned above is a range of imaging modalities and processing techniques. Applications of intelligent systems within the medical industry have received a lot of interest. This is mainly due to the ideal nature of these systems to be applied to highly variable products. Through out the literature, intelligent systems have been reported to perform better than traditional methods for model approximation, segmentation and decision control.

Three dimensional imaging techniques seem very attractive at first but the amount of information that needs to be processed is rather extensive and most likely would not be feasible in a processing environment. Another issue with obtaining all carcase information at one time is if a carcase moves between or while an operation is performed, the information will become invalid. Even if the carcase doesn't deform, the reference points will still need to be relocated, causing operations to be repeated. To get around these problems, approximate overall data should be obtained and used to make approximate decisions while operations are being performed. More detailed information of smaller areas should be obtained in real time to correct the original approximation. This procedure would allow most of the information to be computed in parallel and a lot less memory would be required per task.

A range of imaging modalities would be used to enable the exploitation of each of their advantages. Suitable imaging techniques used in the medical industry include, ultrasound, radiometry, digital Xrays and digital cameras. Even sensors to feel stiffness changes could be used to locate bone interfaces near the surface.
To approximately map out the carcase structure, plain Xrays and digital photos can be used. If coupled with expert knowledge in the form of a fuzzy system, an approximate topology of the carcase can be obtained. Once an approximate mapping is created, more detailed information can be obtained from the predicted area. Detailed information will need to be obtained in real time while various processes are undertaken.
Breaking down the carcase into various segments is an ideal operation for a fuzzy system or a neural network. An atlas based segmentation system can be used to create fuzzy rules and make approximations on the sizes of various parts of a carcase based on expert knowledge. Patterns based on various identification points/variables can be approximated by a suitable neural network.

Due to the complicated nature of a carcase a whole system of approximations will be needed, (location of points to be used, processing those points, dynamic visioning etc.) By obtaining variety of simple information from various modalities, a lot of information can be extracted and processed quickly in parallel. By using information from various perspectives cross validation becomes possible.

To implement such a system, a hierarchy of simpler systems will need to be created, each performing a particular task. The information can be obtained by various modalities, each detailed image being processed on a local level. This information can then be passed up to higher levels to combine the lower level information gained from the various modalities to make decisions on how to implement the desired outcome. The overall system could even be monitored by an expert system to make sure the automated solution is within reasonable bounds.

Obtaining highly detailed, three dimensional information is one thing, but the usefulness of this raw data is another. Most of the full three dimensional imaging modalities would not be able to meet the time constraints of a processing environment, (with the exception of ultrasound and

maybe PAT/TAT). The idea of sacrificing image quality for dynamic real time images has been realised in the medical industry. During IGS, real time ultrasound and fluoroscopy are used more often used than CT and MRI images taken prior to surgery. Many organs in living beings are dynamic, placing more weight on the real time advantages for some medical procedures.
In a processing environment, real time decision making will eliminate the need for excess machinery to keep the carcase in the same position throughout the process.

For the detection of nodules, investigations regarding microwave based imaging have been identified as having more potential than density based methods. More detailed information about the tissue has been able to be obtained due to the higher contrast possible using microwave based imaging. Further investigation regarding the potential and disadvantages of these methods, (mainly TAT and MI) for detecting nodules in live stock is worth while. These techniques may provide a quicker and more robust method than ultrasound.

The meat industry shares many things in common with the medical industry. Where the developments of new technologies are considered for the meat industry, the medical industry should be looked at for solutions to similar problems. Newer technologies may be discovered with a range of benefits over existing technologies that could be implemented into various systems. It would be desirable to use modern technologies parallel to that of the medical industry rather than following it.

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