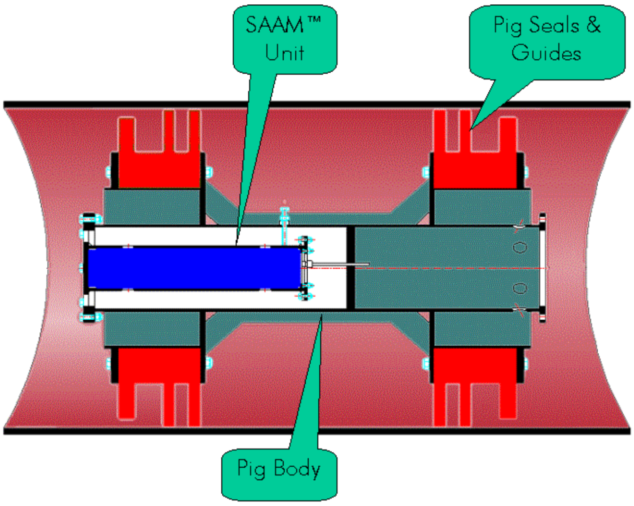
THE SMART ACQUISITION & ANALYSIS MODULE (SAAM™) FOR PIPELINE INSPECTION

1. Comparison of SAAM™ vs. a Traditional Intelligent Pig

Instead of actually physically measuring the pipe wall for a specific feature, using a combination of relatively simple instruments, the SAAM™ unit measures the dynamic behaviour signature of the pig as it travels down the line. Conceptually it can be viewed as the pigs 'black box' flight recorder. Instruments used are:

- Differential Pressure Gauge – measures the pigs true drive pressure.
- +/-2g Accelerometer – measures the pigs linear acceleration and inclination.
- +/-10g Accelerometer (Vibration) – measures the pigs vibration.
- Temperature Sensor.

Diagram of SAAM™ located inside a typical pipeline cleaning pig:



SAAM™ can be used to identify, locate and monitor:

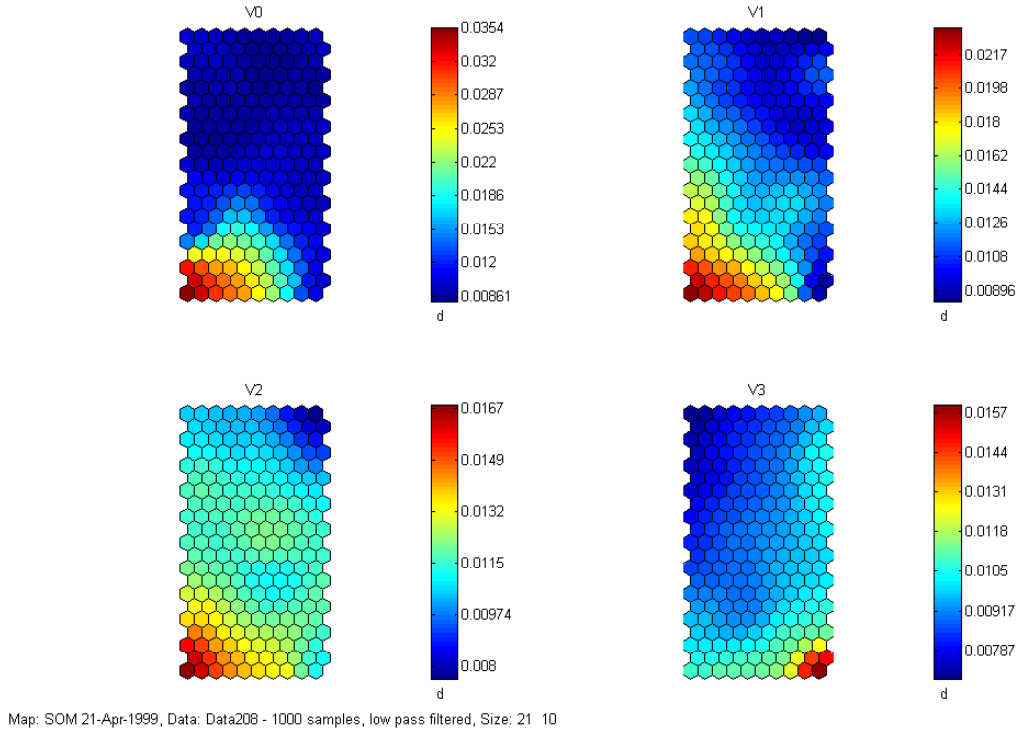
- Dents
- Buckles
- Damage to the pipeline
- Vertical profile/mapping of the pipeline
- Subsidence
- Status of in-line components
- Internal anomalies indicative of surface roughness effects
- Zones of Wax
- Other unclassified anomalies

Summary table of comparison between a conventional intelligent pig, and the SAAM™ method of pipeline inspection:

TASK	CONVENTIONAL INTELLIGENT PIG	SAAM™
Extensive Project Planning	Yes	No
Pre-Inspection Pigging Required	Yes	No
Pig Trap Modifications Required	Often	No
Requirement to Adjust Production Rates	Often	Rare
Level of Risk in Deployment	Often Significant	Negligible
Typical Cost	$ 000's/km	$ 00's/km

2. Software Analysis – Use of Artificial Intelligence

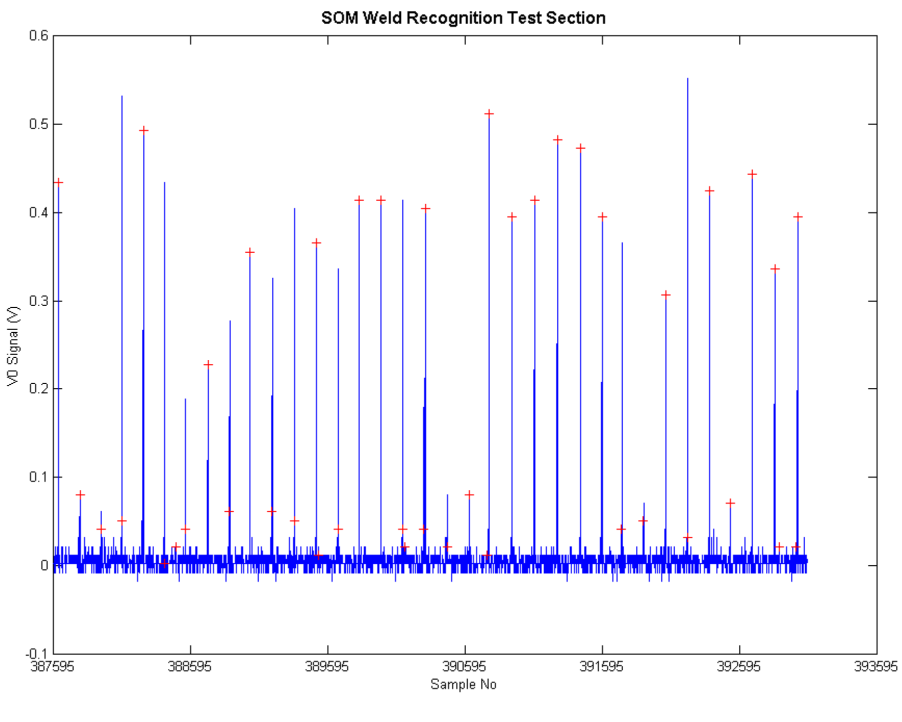
- Data gained from a SAAM™ survey produces large log files.
- SAAM™ method of pipeline inspection is of no use unless this data is successfully interpreted.
- RST' custom built visualisation and analysis software assists in this task.
- In order to improve the efficiency of the analysis process, use is now being made of artificial intelligence techniques.
- Self Organising Maps (SOM's), are being used (SOM - a type of neural network that is useful in the classification of complex, multi-dimensional data). As a result 8 channels of instrument readings from the data file can be organised & mapped as a 2D map. The neural network acts to attempt to ensure that similar input vectors are mapped to locations on the plane which are close together. The output map consists of a number of discrete cells and not a continuous plane. It is important to note the SOM undergoes unsupervised learning, therefore teaches itself to recognise significant features in the data, not by being shown pre-defined classes of input.
- This approach has been applied to weld recognition. As a pig passes a pipe spool girth weld, the pig kicks in a characteristic fashion, which is recorded by the vibration sensor on the SAAM™ unit. Identification & tagging of these welds, enables the pipe to be broken down into individual spools, and thus navigated by Kilometre Posting. The weld recognition SOM has proved successful in identifying & tagging some 95-98% of actual welds. A simple velocity check then identifies where welds have either been missed (local velocity decreases) or incorrectly identified (local velocity increases).
- Best results have been achieved using SOM trained on (nearby) sections of the same survey. The results gradually worsen as one moves further away from the section where the SOM was trained.
- Attempts at using maps trained on earlier surveys, to classify data from subsequent surveys, have thus far proved erratic. Sometimes they are good, and other times they are not.



- The figure above represents the self-organised map created for weld recognition. It should be noted that the figure shows four views of what is a 4-D object and not four different objects. From the map it is clear that the neural network is clustering samples that have high V0, V1, and V2 values in the bottom left hand corner of the map. It is noticeable that the high V3 values fall in the bottom right hand corner, suggesting that they are a poor indicator of the position of welds.

- Welds were classified by constructing a list of sample numbers that the SOM mapped to a group of thirteen cells in the bottom left hand corner of the map. The figure below shows the SOM performance on the data. Two possibilities exist for the use of SOMs to classify welds - either a SOM could be prepared from a short section of data, and then used to classify an entire survey, or a new map could be constructed for each section of the survey.

Chart shows the SOM's performance in identifying welds in a section of pipe from an actual survey:



- A wax recognition SOM has also been used. The data sets used were the mean values of each signal in the part of each pipe joint away from the weld. The trial SOM looks at the absolute values for all eight data channels. The outcome was successful identification of known regions of wax deposition in the pipeline.
- Further work may lead to it being possible to use SOM's to identify the changes in the data recorded from one survey to the next. However, there are problems in ensuring consistency in a number of factors between surveys, that would be required in order to achieve this – such as operating conditions, pig disc wear etc.

Over time greater use will be made of artificial intelligence in the analysis if SAAM™ data, as used properly it can increases the accuracy of the results gained from the data, and vastly decrease the analysis time required.

3. What makes it Possible?

- Memory – 8 data channels sampling at 13hz for 30 hours is a lot of data. Driven by digital camera technology, PC cards enable up to 440mb to be stored in solid-state memory, about the size of credit cards.
- The past 18 months have seen energy densities of batteries increase by around 50%, providing the ability to power SAAM™ for longer periods. SAAM™ draws 100mA @ 7.2v, and uses Nickel Metal Hydride batteries. Rechargeable Lithium batteries will hopefully be used in the near future.
- The development of low power, high performance, true single chip PC's, has provided SAAM™ with the necessary processing power.
- Miniaturisation of all the above, allowing SAAM™ to inspect 8" pipelines. In order to fit into these pigs, SAAM™ cylindrical casing is restricted to 100mm diameter by 381mm, a volume of only 3 litres.
- Testing in pipeline loops, has enabled the correct instrumentation to be evaluated and configured. In addition, testing has enabled the mechanical design of SAAM™ to be optimised, to ensure robustness & reliability.

4. The Future for SAAM™?

- Wider service environment applicability – temperature up to 100°C in short/medium term, 150°C long term, through use of higher temperature resistant components, and by isolating the equipment from the heat.
- Size, down to 6" in short/medium term. Very hard to achieve – current volume of SAAM™ casing is about 3 litres, and that does for 8" line. SAAM™ for a 6" line, would require a volume of less than 1 litre – 1/3 of space in an already crammed environment.
- Further instrumentation – Angular velocity metre, to measure pig movement in the horizontal plane.
- Increased range and memory capabilities
- In house test loop – will allow evaluation of further instrumentation.
- Corrosion – early stage test results suggest that pig behaviour is modified by the existence of internal pipeline corrosion. Further work will establish whether this is indeed the case, and whether it has commercial implications.