The University Defence Research Collaboration In Signal Processing

2013-2018

UDRC

THE UNIVERSITY DEFENCE RESEARCH COLLABORATION IN SIGNAL PROCESSING

2013 to 2018

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Foreword

Signal processing is an enabling technology crucial to all areas of defence and security. It is called for whenever humans and autonomous systems are required to interpret data (i.e. the signal) output from sensors. This leads to the production of the intelligence on which military outcomes depend. Signal processing should be timely, accurate and suited to the decisions to be made. When performed well it is critical, battle-winning and probably the most important weapon which you've never heard of.

With the plethora of sensors and data sources that are emerging in the future network-enabled battlespace, sensing is becoming ubiquitous. This makes signal processing more complicated but also brings great opportunities.

The second phase of the University Defence Research Collaboration in Signal Processing was set up to meet these complex problems head-on while taking advantage of the opportunities. Its unique structure combines two multi-disciplinary academic consortia, in which many researchers can approach different aspects of a problem, with baked-in industrial collaboration enabling early commercial exploitation.

This phase of the UDRC will have been running for 5 years by the time it completes in March 2018, with remarkable results. This book aims to present those accomplishments and advances in a style accessible to stakeholders, collaborators and exploiters.

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UDRC Phase 2 Project Technical Authority

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Chapter 1

Introduction

The University Defence Research Collaboration (UDRC) in Signal Processing is an ongoing academic venture between the UK Ministry of Defence (MOD) and the Engineering and Physical Sciences Research Council (EPSRC). This book describes phase 2 of the UDRC, a 5-year £11.5M programme centred on an £8M grant funded equally by EPSRC and MOD, which ran from 2013 to 2018. The aims of the UDRC are to:

1. develop signal processing science and technology to address military challenges,
2. develop a world class UK skills base in signal processing for defence,
3. form a key component of the wider community of practice in defence signal processing,
4. facilitate the rapid exploitation of science and technology in the signal processing domain to address military requirements.

Phase 2 followed the successful UDRC phase 1, which commenced in 2009, finished in 2013 and explored themes of detection, tracking, classification and multimodal fusion. The phase

2 project was larger both in scope and resource and addressed the topic of *Signal processing in a networked battlespace*. The aims of the UDRC accord well with the objectives of EPSRC, which has the published mission to “Promote and support ... high quality basic, strategic and applied research and related postgraduate training in engineering and the physical sciences, advance knowledge and technology and provide trained scientists and engineers, which meet the needs of users and beneficiaries, thereby contributing to the economic competitiveness of the United Kingdom” [1]. The UDRC’s technical aims further align with the EPSRC’s Digital Signal Processing research area under its Information Communication and Technology theme.

Through the UDRC, MOD’s Defence Science and Technology Laboratory (Dstl) and EPSRC have formed a relationship which benefits both parties as well as meeting the objectives above. The access to deep technical research and senior academics in the UDRC helps maintain the vital technical currency of MOD’s principal internal source of independent scientific and technology advice. Additionally, the relationships formed between UDRC academics, MOD stakeholders and defence industry are key to developing in the minds of the researchers an understanding of real-world constraints and demands.

The UDRC phase 2 was composed of a pair of consortiums, one based in Edinburgh (Edinburgh University and Heriot-Watt University, joined in 2016 by Queen’s University Belfast: the Edinburgh Research Partnership or ERP), and the other originally made up of four universities (Loughborough, Strathclyde, Surrey and Cardiff: LSSC). LSSC became LSSCN in 2015 following the consortium lead Professor Jonathon Chambers’ installation as Head of the Communications, Sensors, Signal and Information Processing Group at the School of Engineering at Newcastle University. Edinburgh University is responsible for UDRC-wide coordination activities such as the management of the website and organisation of the annual conference. Each consortium had a steering group (known as the Consortium Steering Group: CSG at LSSCN and Strate-

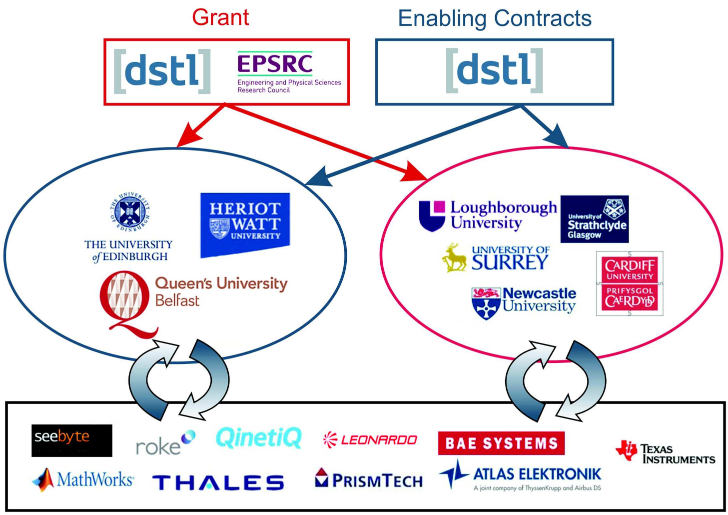

Figure 1.1: UDRC phase 2; composition of each consortium and links with funding bodies and industrial partners

gic Advisory Group: SAG at ERP) with representation from senior academics, industry (both defence primes and small and medium enterprises), Dstl and EPSRC, as well as independent advisers with longstanding defence signal processing expertise. This balance was important as it ensured that the projects achieved the best combination of academic excellence, defence relevance and a high likelihood of industrial exploitation. The composition of each group is shown in table 1.1 and illustrated in figure 1.1. The figure also shows the grant from EPSRC and MOD distinct from subsequent MOD funding (see §1.2.1).

The UDRC phase 2 supported 24 academic staff, 28 Research Associates (RAs) and 4 project management staff. During 2013 to 2018 over 20 PhD students have worked on UDRC projects.

Each consortium's programme of work covered a number of individual projects. In most cases these were run by an

Table 1.1: Composition of the steering groups of the LSSCN (Loughborough, Surrey, Strathclyde, Cardiff, Newcastle) and ERP (Edinburgh Research Partnership) consortiums

	LSSCN	ERP
Independent expert(s)	Prof. Moeness Amin (Villanova U.) Alan Gray (ex Royal Signals, DERA) Prof. Edward Stansfield (ex Thales)	Prof. Alfred O. Hero (U. Michigan)
Industry	Atlas Elektronik Kaon Leonardo The Mathworks Prismtech QinetiQ Thales Texas Instruments	BAE Systems Leonardo Roke SeeByte QinetiQ Thales
Government	EPSRC Dstl	EPSRC Dstl
Universities	Loughborough Strathclyde Surrey Cardiff Newcastle	Edinburgh Heriot-Watt Queen's Belfast

RA with academic staff retaining control of the research direction. Each project was overseen by Dstl whose staff were tasked with identifying exploitation routes via a MOD programme or other route. Projects were grouped into research *themes* loosely aligned to common sensor signal processing tasks. These tasks ranged from processing which occurs close to the sensor front end (e.g. compressive sensing), through higher level activities like detecting threats and anomalies, to implementations in hardware. The list of projects grouped by research theme

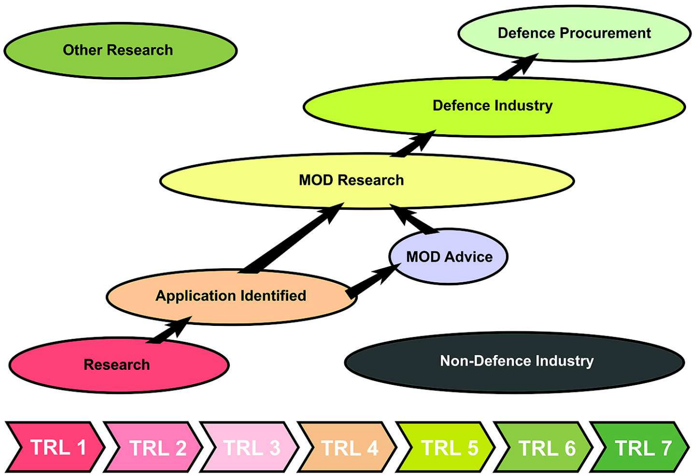

Figure 1.2: The UDRC's exploitation model

is shown in table 1.2. More details of the work undertaken in each theme is given in chapters 2 – 6.

1.1 Exploitation

The UDRC's research activities are, by design, low Technology Readiness Level (TRL 1 – 4). Exploitation of this kind of fundamental work often takes a long time and goes through many steps of validation, concept refinement and benefit assessment. Therefore, the traditional metric of military exploitation only having occurred when the technology in question is in-service in military equipment is too blunt to measure the utility of UDRC research, and does not capture alternative exploitation paths such as commercial exploitation and support to MOD advice and decisions. The UDRC uses a richer model, as illustrated in figure 1.2, to capture milestones along the path of exploitation. The following describe select categories from the figure in more detail.

Table 1.2: Current exploitation stage of each of the UDRC phase 2 projects divided according to research theme (and associated chapter) with exploitation routes identified. Key for exploitation stage column: App. Id – application identified, MOD R. – MOD research, MOD Ad. – MOD advice, D. Ind. – defence industry, D. Pr. – defence procurement.

Theme	Cons.	Project	Stage	Exploitation
Sensing and signal separation (Ch. 2)	ERP	Compressive sensing	MOD R.	Electronic surveillance
			D. Ind.	Radar imaging
			D Pr.	Raman spectroscopy
	LSSCN	Signal separation	MOD R.	Audio blind-source separation
		Beamforming	D. Ind. MOD Ad.	Sonar arrays
Multi-sensor methods (Ch. 3)	LSSCN	MIMO radar	Industry	Cognitive radar
			D. Ind.	Radar ATR
	ERP	MIMO sonar	MOD R.	Underwater object classification
			D. Ind.	
		Sensor registration	D. Ind.	Deployable sensor networks
		Distributed detection	App. Id	Tracking faint targets
Sensor management (Ch. 4)	ERP	Sensor management for tracking	MOD R.	Space situation awareness
				Maritime sensor fusion
	LSSCN	Inference with domain knowledge	D. Ind.	CBR source term estimation
		Uncertainty in game theory	Research	Radar waveform design
			App. Id	Multi-target tracking
Threat refinement (Ch. 5)	LSSCN	Statistical anomaly detection	D. Ind.	Maritime SA
			MOD R.	Behaviour recognition
		Anomaly detection in networks	MOD R.	Cyber defence
	ERP	Anomalous behaviour detection	MOD R.	Wide-area motion imagery
Implementation	ERP	Efficient computation	Research	Image classification
(Ch. 6)		Distributed algorithms	MOD R.	Distributed ES
	LSSCN	Low-complexity algorithms	D. Ind.	Large sonar arrays

- Research: fundamental or applied research conducted in universities. Funding will generally come from the Research Councils. Exploitation at this level will mean a continuation of the UDRC research in areas linked directly or indirectly with the UDRC.
- Application identified: MOD, or industry partners, have identified an exploitation route for UDRC research. Dstl and industry work with researchers to understand the implications of the chosen scenario for algorithm development, and the effort involved in their transplant.
- MOD advice: the use of UDRC outputs to provide advice and guidance to MOD through studies, reports, technology roadmaps, horizon scanning. Sources of finance include MOD Chief Scientific Adviser (CSA) funding.
- MOD research: the research undertaken in the UDRC is taken on and developed further, perhaps toward a standalone or integrated demonstration, in an applied research project. Sources of finance come from MOD CSA, including Dstl funding and Defence and Security Accelerator (DASA) projects.
- Defence industry: the incorporation of UDRC technology into a product manufactured by industry. Industry generally uses its own funding to engineer the system that carries the UDRC output.
- Defence procurement: UDRC research output exists, at a high TRL level, in a product procured by MOD.

During UDRC phase 2, Dstl's brief has been to understand each project's aims and match them to relevant military requirements. Dstl has worked with academics to move towards exploitation by using such things as real data, relevant scenarios, real-world constraints or realistic noise and clutter models, and made the link back to MOD capability advisers or requirements owners.

As phase 2 matured and with projects developing at differing paces, individual project requirements became less homogeneous. Dstl has been proactive in matching opportunities to the exploitation status of the research. In some instances this meant supporting TRL-raising activities and technology demonstration. There are other projects, however, where the task amounted to understanding the academic concept so that deep technical understanding informed advice to MOD. UDRC – MOD interaction increasingly became supported by directed contracts (see §1.2.1). This reflected the fact that Dstl's job was not just to 'get the word out' to prospective funding streams. Rather MOD projects with a signal processing need have come to know that the UDRC is a viable route by which novel technologies can be developed, and are keen to undertake direct exploitation of UDRC research.

All UDRC phase 2 projects have undertaken *exploitation campaigns*. These time-bounded applications of academic research (typically over the course of 12 – 18 months) to a particular problem area ensured UDRC researchers considered a real-world scenario. Such campaigns brought benefit both MOD and academic researchers by introducing diversity and impact into the research programme and allowed Dstl to identify multiple relevant exploitation routes. Campaigns have been supported by data sets and metrics from the relevant application area. Two illustrative examples of research applied in different campaigns are:

- distributed data fusion for accurate registration of sensors applied to sonobuoys and SAPIENT networked base protection sensors (see §3.3);
- inference using domain knowledge has been shown by UDRC researchers to better track ballistic missiles, and is a method being developed for CBR source term estimation overseen by Dstl's Hazard Assessment Simulation and Prediction Group (§4.1).

There are examples across all projects – looked at in more detail in the following chapters. Exploitation campaigns are listed in table 1.2 with an estimate of the position in the exploitation model as shown in figure 1.2.

1.2 Defence development and advice

These activities support the strategic objective to exploit signal processing science and technology to address military requirements.

1.2.1 Enabling contracts

Within the UDRC phase 2, in addition and in parallel to the EPSRC grant, a flexible contract tasking framework between Dstl and each consortium was established. This provides Dstl with the ability to direct researchers from either consortium to focus on emergent short-to-medium term defence-specific signal processing problems. These projects are aimed at raising the TRL of the research from 1 – 3 to 4 – 6. The objectives of this contracting framework are:

- to further develop and refine research carried out under the wider UDRC signal processing programme, to more sharply focus on defence-specific problems;
- to provide support and assistance to the independent technical review and assessment of signal processing elements included in other parts of MOD's research programme by providing access to the deep technical expertise within the academic consortiums.

These contracts, totalling over £750k, have allowed Dstl projects rapid access to the output of UDRC research, for example to modify and specify algorithms to a defence need, or to provide advice on the deployment of a technique in a particular scenario. They represent additional value that the UDRC has

Table 1.3: Projects let through the UDRC enabling contracts

Project title	MOD exploitation	University	Academic Lead
Tracking and association: state of the art review	Image processing and tracking	Heriot-Watt	Clark
Application of novel track and association methods for space situation awareness	Space situation awareness (SSA)	Heriot-Watt	Clark
Innovative underwater track motion analysis concepts	Maritime freedom of manoeuvre	Heriot-Watt	Clark
Raman spectroscopy of mixtures of chemicals	Explosive substances detection and identification (ESDI)	Edinburgh	Davies
Tracking and association	Image processing and tracking	Heriot-Watt	Clark
Deconvolution of Raman spectral mixtures (phase 2: application)	ESDI	Edinburgh	Davies
Temporal anomaly detection	Undisclosed	Heriot-Watt	Robertson
Mobile Ad-hoc Sensor Networks	Electronic surveillance	Edinburgh Heriot-Watt	Thompson Sellathurai
Tracking techniques for tracking objects in geostationary orbit	SSA	Heriot-Watt	Clark
Self-localisation techniques	Maritime situation awareness	Heriot-Watt	Clark
Raman spectral analysis (phase 3: consultancy)	ESDI	Edinburgh	Davies
Temporal anomaly detection	Undisclosed	Loughborough	Lambotharan

added over and above its £8M base cost. Table 1.3 gives details of the projects.

1.2.2 Knowledge Transfer Meeting

The UDRC Knowledge Transfer Meeting is an annual event, held over the course of a day at Dstl Porton Down, which facilitates two-way knowledge exchange between Dstl subject matter experts and UDRC academics. The meeting evolved a format by which the meeting is divided into two parts, with university partners initially presenting their work in open session. Subsequently, Dstl runs workshops where government and academic scientists brainstorm solutions to MOD problems of current interest or future capability need. The outputs of the workshops have been used as a basis to refresh UDRC technical challenges, and have also informed exploitation through core research, enabling contracts or in understanding emerging MOD signal processing requirements. During the five years, workshops covered such topics as audio source separation, information fusion for classification, spectral unmixing, multiple-input multiple-output methods, sensor registration, tracking of extended targets and signal processing for data science.

1.3 Advancing science and technology

Alongside direct uptake by MOD, the UDRC has addressed its first aim by facilitating the development of science and technology in the signal processing domain to tackle military challenges. Various activities have increased the interaction between academic and applied endeavours, furthering the state of the art in signal processing when applied to defence problems.

1.3.1 Sensor Signal Processing for Defence conference

The UDRC holds an annual open international conference: Sensor Signal Processing for Defence (SSPD), continuing the practice established during phase 1. SSPD is an unclassified conference and provides an opportunity for signal processing scientists from the international community to present their latest findings to fellow researchers and practitioners, and publish in peer-reviewed literature. The emphasis of the conference is given to areas that play a substantial role in improving the performance of military systems. Topics include, but are not limited to array signal processing; image processing; radar, sonar and acoustic signal processing; multimodal signal processing; multi-target tracking; data fusion; sensor management; source separation; target detection and identification; distributed signal processing; low size weight and power solutions.

Technical sponsorship is provided by the IEEE Signal Processing Society and proceedings are indexed on IEEE XPLORE [2]. There are defence and academic keynotes, and the conference also includes both industry and military panel discussions. During UDRC phase 2 the SSPD has attracted high quality international academic keynote speakers from, among others, the US Army Research Laboratory, Australia's DST Group, Ohio State University, Fraunhofer FKIE, Delft University, the University of Naples, Villanova University. These have been in addition to UK keynotes from MOD and Dstl.

1.3.2 UDRC Summer School

The UDRC runs an annual summer school. The aim is to offer an excellent taught signal processing course pitched at Masters level. The course attracts researchers in defence, industry, government and academia with interests in signal processing. Experience gained from the first UDRC summer school in 2013 indicated that a limit of 50 students offers optimal conditions for productive study, and so entrants must apply to attend. The course is divided into four one-day modules allowing a range of signal processing topics to be covered at pace. To ensure that participants are equipped to apply this work to practical solutions, the summer school is delivered through traditional lectures and tutorials on set exercises supervised by leading experts from across the UK signal processing community. In addition, the school has included invited international speakers discussing advanced topics. The objectives of the school are to:

- fill gaps in knowledge for signal processing engineering research students and industrial and government practitioners,
- facilitate the process of taking new theoretical developments into practical engineering applications,

- stimulate new collaborations in this field,
- educate and enthuse the next generation of signal processing experts.

Phase 2 UDRC summer schools are listed in table 1.4. In all years the school has been oversubscribed, and during the phase 2 period MOD alone has sent over 50 students. The course has also proved popular with UK industry and has even seen attendees from US and European government labs. The impact on students is not only improved signal processing research and development expertise but also a deeper appreciation of techniques to address problems in topics with broad defence application like detection and tracking, compressive sensing, anomaly detection, and source separation. From a government point of view this results in more effective oversight of contracted work in these areas. Furthermore, attendees are made aware of developments in the state of the art which allow government and industry projects to benefit from the latest algorithmic developments in signal processing.

1.3.3 Theme Meetings and Challenge Workshops

Theme meetings are held twice a year; a list is given in table 1.5. These are designed to bring researchers together to look deeply at a set of problems linked by a common signal processing technical theme. These meetings have been 'closed', in that they are restricted to members of the UDRC only and fall under the terms and conditions of the consortium agreement. This allows researchers to present findings and benefit from feedback at a very early stage without consideration of intellectual property or the need to prepare results for publication. Attendance and presentation from industry partners and Dstl is invited and this opportunity has been enthusiastically accepted. This has created an atmosphere of collaboration focussed on realising the potential benefits of the technology. Selected themed meetings have been more open, when it was clear that the UDRC would

Table 1.4: UDRC summer schools: dates, locations and topics covered

Dates	Location	Topic
22-26 Jun 2013	Heriot-Watt	Finite set statistics
23-27 Jun 2014	Heriot-Watt	Tracking; Compressive sensing; Anomaly detection; Source separation
20-23 Jul 2015	Surrey	Statistical signal processing; Tracking; Pattern recognition and classification; Source separation
27-30 Jun 2016	Edinburgh	Statistical signal processing; Tracking; Pattern recognition and classification; Source separation
26-29 Jun 2017	Surrey	Statistical signal processing; Radar processing and tracking; Machine learning; Source separation and beamforming

benefit from interaction with another research community. For example, the meeting on "Signal processing for autonomous systems" in 2014 was held jointly with researchers from the Autonomous Systems Underpinning Research (ASUR) project. Similarly, the meeting on "Data science, signal processing and defence" in November 2017 was hosted by the Alan Turing Institute, a major focus for UK academia's data science efforts.

Dstl ran *Challenge Workshops* during theme meetings. This initiative consisted of presentations of military signal processing problems together with data and a challenge objective. Researchers competed against each other to provide the best solution to the Dstl problem before the challenge deadline (usually 8 – 12 weeks from the date of the themed meeting). The competitions often began with a syndicated discussion session where the UDRC researchers brainstormed ideas to address the problems. These sessions were valued by the participants for the inspiration and problem awareness that they brought. Com-

Table 1.5: Theme meetings during the UDRC phase 2

Date	Location	Theme
31 Oct 2013	Edinburgh	Source separation and sparsity
28 May 2014	Surrey	Anomaly detection
10 Nov 2014	Heriot-Watt	Signal processing for autonomous systems (joint with the ASUR project)
29 May 2015	Strathclyde	MIMO and SAR
24 Nov 2015	Strathclyde	Hardware and implementation
17 May 2016	Cardiff	Image and video processing
23 Nov 2016	Heriot-Watt	Space and tracking (joint with the UK Astrodynamics Community of Interest)
16 May 2017	Newcastle	Underwater sensing, signal processing and communications
29 Nov 2017	Alan Turing Institute	Data science, signal processing and defence (joint with the Alan Turing Institute)

petition entries were assessed according to an openly available marking scheme and winners were awarded a prize which, while having negligible value, was nevertheless unique.

Results from the challenges were fed back by Dstl into the originating MOD project, providing the researchers with a chance to showcase potential solutions on a very short timescale. While not a promised outcome, worthy entries often spawned a follow-on project with Dstl, via the enabling contract mechanism (§1.2.1). Previous and current challenges are detailed in table 1.6. Highlights from specific challenges are expanded on in chapters 2 – 6.

1.3.4 UDRC publicity

The UDRC website [3] has been up and running since the inception of the UDRC. Analysis shows that web site traffic is generally evenly distributed throughout the year with increased activity coincident with UDRC events – summer school regis-

Table 1.6: UDRC Challenge Workshop subjects, deadlines, winners and exploitation routes

Challenge	Presented	Deadline	Winner	Exploitation
Spectral deconvolution	Oct 2013	May 2014	Wu, (Edinburgh)	Non-disruptive hazardous substrance identification
Cyber situation awareness	Oct 2013	May 2014		Network surveillance and cyber defence
Wide-area motion imagery anomaly detection	May 2014	Apr 2015	Baxter, (Heriot-Watt)	Aerial surveillance
Ground-penetrating radar anomaly detection	May 2014	Oct 2014	Yaghoobi, (Edinburgh)	IED detection
Underwater Automatic Target Recognition	Nov 2014	Jan 2015	Yu, (Loughborough)	Maritime mine countermeasures
Temporal anomaly detection	Nov 2014	Mar 2015	Lambotharan, (Loughborough)	Not disclosed
Synthetic aperture radar processing	May 2015	Oct 2015		Target detection in radar
Golden Dongle	May 2015	Sep 2015	Thompson, (Edinburgh)	Electronic surveillance
Raspberry Pi	Nov 2015	Apr 2017	Weiss, (Strathclyde)	Electronic surveillance
Occlusion detection (set by Roke)	May 2016	Nov 2016		Imagery processing
Orbital object tracking	Nov 2016	Jun 2017		SSA

tration and conference submission in particular. Under two-thirds of visitors are UK-based, indicating that there is significant international interest. The largest contributors among these are France, USA, India and China. The most popular page is the SSPD conference front page. The website contains links to the phase 1 of the UDRC thus ensuring continuity with previous work and researchers. This helps to foster a single defence signal processing academic community. In December 2014 the first biannual UDRC Newsletter was sent out to all those affiliated with the UDRC and those who have subscribed to UDRC updates, informing the recipients of important dates and links to events.

1.3.5 Non-defence applications of UDRC research

Although the UDRC exists primarily to develop science and scientists for defence-related applications, there are numerous opportunities for the exploitation of the developed techniques in areas outside the defence sphere. This chimes well with EPSRC's broad remit, as well as MOD's additional strategic priority to contribute to the UK's prosperity and UK wealth creation. Non-defence applications of UDRC research are shown in figure 1.3 together with a mapping from UDRC research to application area. The areas align broadly with EPSRC's strategic themes. Mapping exercises such as this one provide assurance to MOD's civil-sector partners that the funded research has a broad scope and strengthens the case for ongoing collaboration and further funding opportunities.

The following chapters expose in detail the work undertaken during phase 2 of the UDRC. Chapters are organised by research theme as in table 1.2. The book concludes with a summary of highlights and makes recommendations for the future.

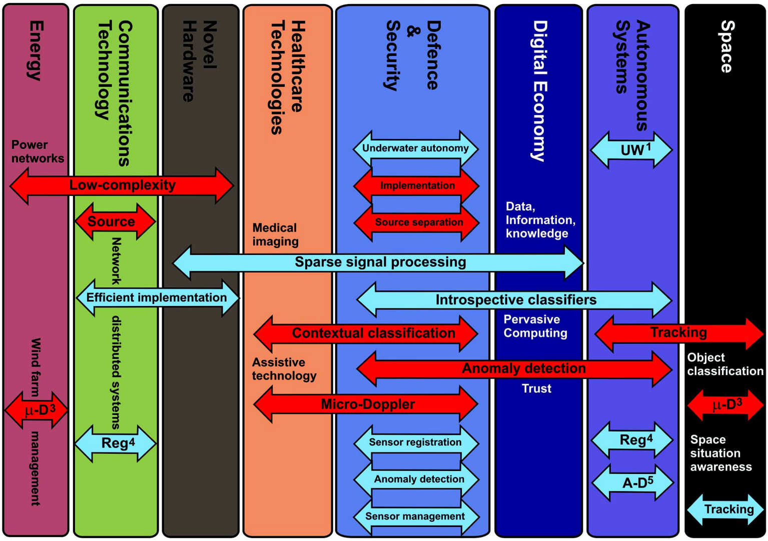

Figure 1.3: UDRC research in areas broadly aligned with the EPSRC strategic themes (columns). Horizontal arrows represent the research output from ERP (blue) and LSSCN (red). Abbreviations are 1, underwater robotics; 2, source separation; 3, micro-Doppler; 4, sensor registration; 5, anomaly detection.

References

[1] Engineering and Physical Sciences Research Council. (2013). Mission and vision, [Online]. Available: https://www.epsrc.ac.uk/about/facts/mission.

[2] IEEE. (2018). IEEE Xplore digital library, [Online]. Available: http://ieeexplore.ieee.org/Xplore.

[3] The University Defence Research Collaboration in Signal Processing. (2013–2018). UDRC website, [Online]. Available: http://mod-udrc.org.

Chapter 2

Sensing and signal separation

Extracting signals of interest and suppressing interference from corrupted sensor measurements remain fundamental challenges in many networked battlespace applications. Phase 2 of the UDRC has sought to develop robust, low-complexity algorithms for signal separation and broadband distributed beamforming. The focus has been on low-rank and sparse representations, and their fast implementation.

Sparse representations seek to approximate signals of interest using a relatively small number of significant components. They are integral to state-of-the-art processing for coding, source separation and compressive sensing. While the basic framework of compressive sensing is well defined, its potential in practical sensing and imaging scenarios still needs to be realised. The UDRC has understood how these techniques can incorporate sensor-specific signal structures within the sensing strategy and accommodate sampling constraints imposed by the sensing physics and operational use. The UDRC has investigated applications in compressive imaging, spectroscopy and large array processing.

2.1 Sparse representations and compressive sensing

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Sparse signal modelling can overcome some of the conventional limitations in sensing and imaging. UDRC research in this area has focussed on radio frequency (RF) and spectroscopic signals.

In electronic surveillance (ES), conventional sampling techniques for wideband sub-Nyquist radar ES are not practical because they are expensive and power hungry. UDRC researchers have developed a new low-complexity sampling technique, inspired by compressive sensing technology, which can overcome these obstacles.

Work focussed on exploiting sparsity for synthetic aperture radar (SAR) looked at phase ambiguity of the radar returns in SAR and proposed a novel technique which compensates for these errors. This research continued from UDRC phase 1 and is an essential element for volumetric SAR imaging. UDRC researchers have also investigated the problem of SAR Ground Moving Target Indication (GMTI), where the moving targets are few with respect to the size of the scene. Moving objects generate blurring and displacement in SAR images and such artefacts have to be compensated for in forming the correct static background image and to accurately locate the targets.

Sparse approximation has also been used for spectral decomposition of Raman signals.[1] The immediate application of this method is in hand-held Raman spectrometers. The aim here has been to build a fast algorithm to identify mixtures of elements. This algorithm was further developed for use on two in-service spectrometers.

2.1.1 Compressive electronic surveillance

Conventional sensing systems often assume some general properties of the signals in order to decide how fast information needs to be collected. This is normally based on the band-limited property of the signals for which the Nyquist sampling paradigm[2] tells us the minimum sampling rate. Unfortunately, the Nyquist rate is often unattainable when signals vary rapidly, as can be the case in ES applications. Equipment to fulfil that requirement can be expensive, power hungry, heavy and large.

For radar ES it is necessary to monitor a large segment of the RF spectrum in order to detect and identify threats. Not only is the design of extremely high rate analogue-to-digital converters (ADCs) very difficult, but powerful processing units to extract information are also required. In addition, reliable and fast recovery and detection algorithms are needed in the processing unit.

Moreover, radar ES signals are wideband and normally exceed the sampling rate and dynamic-range of standard ADCs. To sample such signals one can use a bank of sub-Nyquist ADCs, each delayed by a suitable time increment. This is called a *time-interleaved* ADC [1]. The most important prac-

[1] Raman spectroscopy is a non-destructive means by which unknown mixtures of chemicals can be identified. It relies on observing the spectroscopic response of a material when stimulated by monochromatic light.

[2] The Nyquist rate is a fundamental result in signal processing theory. It states that any bandwidth-limited signal may be completely characterised by sampling at a rate of twice the highest frequency in the signal. It establishes a sufficiency criterion whereby additional sampling of a signal is unnecessary.

tical issues with such a large bank of parallel channels are the feasibility of implementation in terms of size, weight and power (SWAP), and calibration. It is generally preferable to use only a few channels to trade off accuracy against complexity.

Time sharing methods are techniques which use a single, or a few parallel channels. In channelised time-sharing (also called rapid frequency sweeping), a bank of bandpass filters is used to consecutively sample the output of one or a few channels. The main drawback of channelised time-sharing methods is that they only monitor a particular part of spectrum at any time. This makes such techniques ineffective for the detection of short-pulse signals.

Time-sharing techniques fit within the more general framework of sub-Nyquist sampling methods. Time-sharing is one of the simplest, but not the most effective, approaches. There exist other sub-Nyquist techniques for signal sampling [2]. These techniques partially compensate for artefacts caused by sub-Nyquist sampling by using a non-uniform periodic sampling scheme. Since a linear reconstruction technique is used, some error in the sampled signal remains.

The UDRC approach to the problem of sub-Nyquist sampling is based on compressive sampling of signals [3], [4]. Different variations of this method have been studied for continuous-time signals [5]–[7]. One such framework, [7], was developed and applied to the problem of wideband RF signal sampling, targeted at radar ES applications. Most compressive sub-Nyquist sampling techniques need some non-linear reconstruction techniques. This leads to a problem because canonical reconstruction techniques are not always suitable for large scale problems (like radar ES) owing to their high computational complexity.

The UDRC solution uses only a few ADCs; this is called a multi-coset sampling system [7]. It is a low-complexity algorithm for the recovery of full-band input signals. As an approach to wideband RF sampling it has potential in air or maritime ES, with application to early warning, jammer detection and the detection of target signatures. The advantage of this method is in its low hardware cost, simple signal processing and digital calibration capability.

The proposed ES system was tested with synthetic data generated by a simulator produced by Thales UK, demonstrating good balance between performance and the complexity of the hardware. In general, the trend in the latest generation of ES systems is to have a higher computational complexity, but significantly better performance. A comparison of the proposed multichannel sub-Nyquist system (where there is a greater computational budget) with the next generation of ES systems is essential and is a recommended next step.

2.1.2 Volumetric SAR with compressive processing

SAR is a widely used weather-independent day-or-night remote sensing tool for high resolution imaging. Volumetric SAR imaging is challenging as multiple passes of radar data must be combined coherently to generate 3D-images. This process requires very precise position measurement during multiple flight passes, which is not easily achievable. Two important issues are, (i) errors in the recorded locations and (ii) undersampling in the height dimension. Both of these can be reformulated as compressive sensing problems. In the first, the range estimation errors can be interpreted as errors in pulse compressed signals. Compensation for such errors can be tackled with sparse phase recovery methods. The second issue is related to more conventional compressive sensing where the properties of a compact target (which only occupies a small part of the volumetric image) are exploited.

The source of inaccurate range estimation is due to two errors: in the platform location and in the scene topography. Range estimation errors induce asynchronisation in the dechirping process, i.e. a shift in the range direction. When such an error is small, the final image will be blurred and can be compensated for using conventional autofocus techniques.

In multi-pass SAR image formation the error between passes can be so large that a different correction method is needed.

The range estimation error appears as a structured phase error in the phase history. This means that the received radar pulses at different heights cannot be coherently integrated to add the third dimension to SAR images. A new phase recovery technique for compensating the phase error has therefore been developed. The technique uses the Gerchberg-Saxton algorithm [8]. The phase is gradually refined by alternating between different representations of the data. This standard technique has been modified for volumetric SAR because the forward and backward operators are not orthogonal [9].

The basic method for correcting range estimation errors is manual using a reference target in the scene [10]. The UDRC-developed method provides an alternative for more realistic situations when there is no reference target. This range error calibration, through a phase recovery formulation, is a powerful framework which shows good performance in comparison with the more conventional manual correction approach. There is also a potential for phase recovery in asynchronous SAR systems, e.g. SAR imaging for automotive sensing, which uses relatively inexpensive sensors.

Another challenge in volumetric SAR is the anisotropic nature of the target components. This property of the targets only allows a limited integration of the radar pulses, otherwise artefacts are generated. Identification of a particular target is therefore possible only over a short aperture. Calibrated circular SAR pulses of some civilian cars from the US Air Force Research Laboratory (AFRL) GOTCHA dataset [10] are shown in figure 2.1. These images (which have 30 cm resolution and are projected into 2D) are often good enough to detect the number of car pillars. However, proper volumetric imaging of the cars is only possible if enough pulses are integrated from multiple passes to achieve vertical resolution and data such as that in figure 2.1 can help to achieve this.

In the process of developing fast calibration techniques UDRC

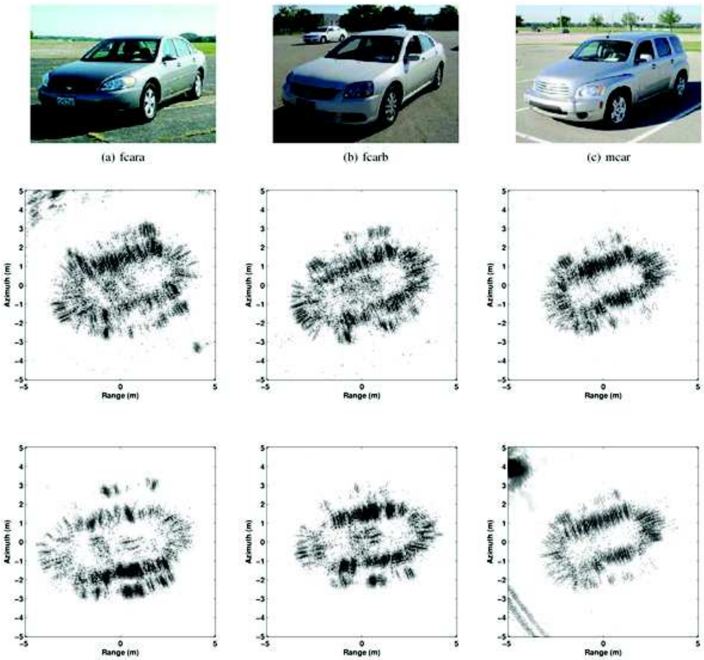

Figure 2.1: Cars and their SAR images at 0 m elevation: (a) Chevrolet Impala LT, (b) Mitsubishi Galant ES and (c) Chevrolet HHR LT; data from [10]

researchers also implemented fast forward-backward projections to run on graphics processing units (GPUs). Such implementations accelerate the image reconstruction process and can be used in other applications of compressive sensing in SAR.

Fast synthetic aperture radar imaging with back-projection: a project with industry

Through a contract with Leonardo (Selex ES at the time) UDRC researchers prepared a SAR data processing pipeline. This package took raw radar data, did pre-processing, motion compensation, deskewing, and generated SAR images using

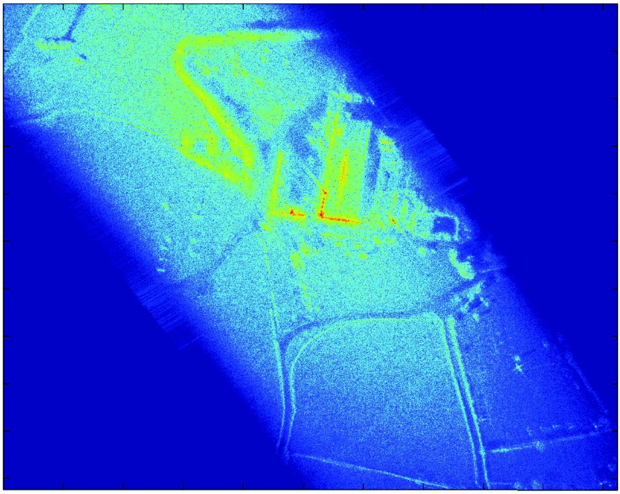

Figure 2.2: Large-scale SAR image reconstruction using fast back-projection with decimation in phase history

back-projection (BP). The algorithm is based on decimation and application of BP to much smaller data. This approach has been used in other domains (e.g. computational tomography). The UDRC method extended the approach to apply the decimation in phase-history or in the image domain. Each approach has its advantages and may be selected to suit a particular setting.

The package was tested at a trial, imaging an airfield. As the example related to a large scene, many reconstruction techniques generated inaccurate outputs. In contrast, the UDRC-developed fast BP algorithm performed well (see figure 2.2).

2.1.3 Sparsity-driven GMTI processing framework with multi-channel SAR

GMTI techniques are of military interest as the ability to locate and identify moving targets is crucial for battlefield intelligence. GMTI in SAR is notoriously difficult, however, as conventional processing methods tend to blur and shift moving targets, often rendering them invisible. This work was originally motivated by introducing a priori information, i.e. sparsities, into conventional SAR and GMTI methods to enhance their performance. The work undertaken by the UDRC eventually expanded into a processing framework with a complete signal processing pipeline to realise multiple GMTI tasks.

Typical SAR-based GMTI tasks are image formation, target detection and the estimation of moving target states (e.g. positions, velocities) using a spotlight SAR geometry (figure 2.3). A terrain map is associated with the illuminated scene. The airborne platform uses multiple radar channels which are equally placed along the flight path. There exist several challenges for GMTI missions in this scenario. Firstly, the moving targets in SAR images will be misplaced and blurred. Therefore, target focussing and localisation methods need to be developed. Secondly, conventional GMTI approaches have been proven to work properly under homogeneous environments. However, for non-homogeneous clutter, such as mountains with large terrain variations and urban regions with strong building reflectors, these methods miss detections and show large estimation errors [11]. Here, extracting moving targets from strong clutter is an open challenge. Thirdly, digital elevation model (DEM) information can significantly influence the SAR and GMTI accuracies; a well-developed GMTI model has to consider the incorporation of elevation data. Lastly, typical SAR and GMTI algorithms are widely known to be computationally expensive. When introducing sparsity into the framework, both estimation accuracy and computational load need to be considered. The proposed framework aims to serve as a generic model for

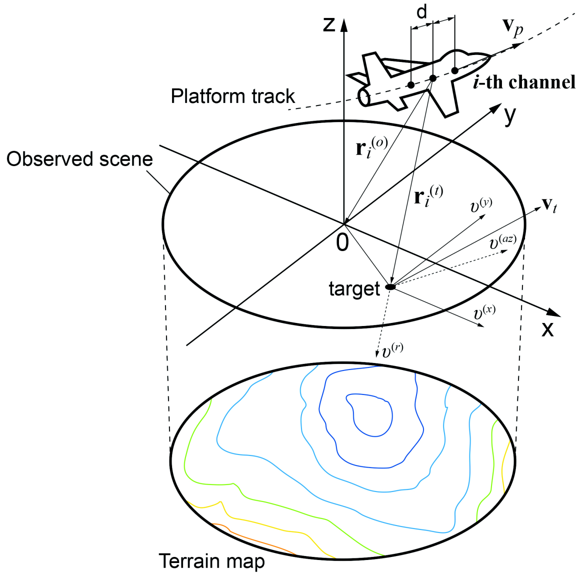

Figure 2.3: Spotlight airborne SAR geometry with multiple channels

tackling these problems which can also incorporate other SAR imaging algorithms.

The target imaging problem was initially investigated by UDRC researchers in [12]. This work was the starting point for generalising the task as an optimisation problem and investigating how sparsity can be used to estimate the state of targets and form SAR images. In this work, only two channels were modelled in extending the conventional algorithm [13] to a sparsity-regularised optimisation problem. Based on real GOTCHA GMTI data [14], the experimental results show acceptable velocity estimation and relocation accuracies. Significant displacements for the target localisation were seen due to elevation variations in the terrain.

Subsequent to the work in [12] which represented a simplified target indication, a more complete algorithm was developed in [15] with a greater number of radar channels. The

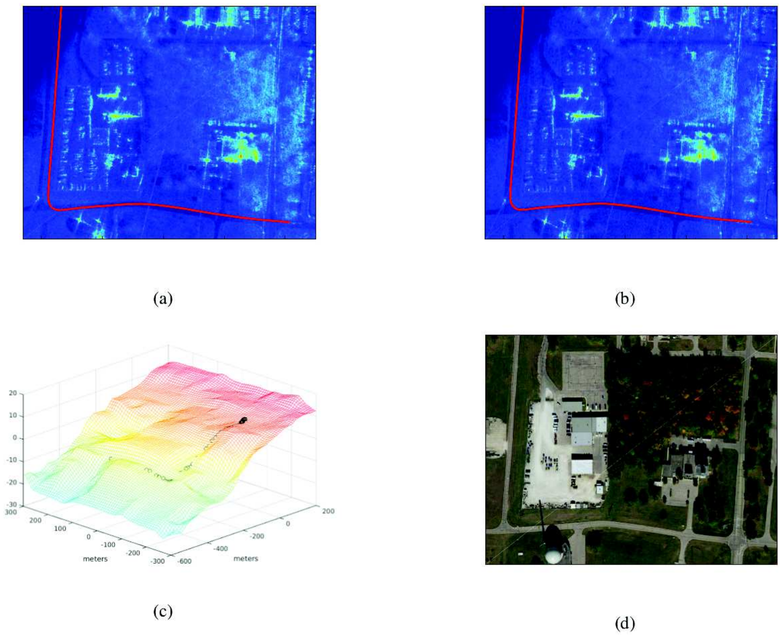

Figure 2.4: (a) and (b) reconstructed SAR images (in dB) using range-gated data (from [14]) to show the GMTI scene without and with the DEM respectively; the red path shows the ground truth target trajectory; (c) the extracted terrain map, the black circles show the target trajectory; (d) the corresponding overhead image of the scene

new method mainly focussed on a well-defined model to realise target detection without state estimation by separating moving targets from background. By modelling the phase differences between channels and utilising the sparsities of the moving targets within an optimisation framework, the raw data was decomposed into dynamic and stationary portions, and the moving and static objects were processed separately. Simulation results demonstrated the ability to separate moving targets from strong clutter.

DEM information plays a vital role in SAR imaging with significant elevation variations. In [16] the UDRC showed how the DEM can be utilised to enhance the localisation of moving targets and improve the estimation of targets' states. In particular, the processing of DEM data and how it fits into the existing SAR algorithms was investigated.

The next stage of the work brought the UDRC-developed SAR-based GMTI components together. These were structured as an end-to-end framework with comprehensive models and theoretically and experimentally proven algorithms. In [17] a processing framework was proposed which separated the moving targets from the clutter under multichannel SAR scenarios, and addressed the moving target imaging and velocity estimation problems for GMTI applications along with a practical two stage processing implementation. The high-level data structures, e.g. sparsity of the moving targets in the observed scene, were exploited throughout the framework. The model was sufficiently versatile to incorporate the DEM information, which further improved the moving target relocation accuracy. The framework was evaluated using the GOTCHA GMTI challenge data (see figure 2.4) and has shown better accuracy than state-of-the-art GMTI methods, e.g. [18]–[20].

2.1.4 Raman spectral deconvolution

Raman spectroscopy is a field-proven method for identification of liquid and solid chemicals which can be used as explosives or chemical warfare agents. The information generated using this method provides identification of the materials present by comparison with reference library spectra. Raman spectroscopy permits non-contact analysis of materials, and established systems have extremely large reference libraries to increase the probability of detection of unknown materials. Limitations of currently available systems include identification of components of complex real world mixtures due to interfering signatures and low signal contributions.

The process of generating an identification response must be fully automated without any user input as the systems may

Figure 2.5: Example scenario where material identification may be of use

be employed in physically stressful environments, an example of which is seen in figure 6.4. There are a range of developments underway to advance the hardware associated with hand-held Raman spectrometers to improve performance and reduce the size and cost of systems. An important aspect of this activity is to generate efficient signal processing capabilities.

Raman spectra typically consist of: (i) spectral peaks from the target which could be pure chemicals or mixtures, (ii) system noise and, in some instances, (iii) sample fluorescence.[3] It is only the spectral peaks which contain useful information. Therefore signal processing approaches need to consider removing, or accounting for, system noise and fluorescence contributions.

The UDRC developed fast sparsity-based spectral deconvolution algorithms suitable for hand-held and low-computational power instruments, to provide near to real-time mixture deconvolution.[4] The algorithms are simple to implement and mod-

[3]Fluorescence occurs upon absorption of the incident light, often in coloured samples when using a visible-wavelength-based Raman system.

[4]In this context a spectral identity should be returned in under 60

ular: different blocks of the processing chain can be replaced if other methods perform better. Early exploitation of this work was demonstrated through the licensing of the approach by UDRC researchers at the University of Edinburgh to Snowy Range Instruments (now Metrohm Raman), a manufacturer of Raman spectrometers.

Figure 2.6 shows results of the novel low complexity sparsity based algorithm used to deconvolve the spectra using a reference library. The algorithm is based on iteratively subtracting the contribution of selected spectra and updating the contribution of each spectrum. The core algorithm is called *fast non-negative orthogonal matching pursuit* [21], which exploits UDRC work on general non-negative sparse representations. The iteration terminates when the maximum number of expected chemicals has been found or the residual spectrum has negligible energy, i.e. of the order of noise. A backtracking step removes the least contributing spectrum from the list of detected chemicals and reports it as an alternative component. This feature is particularly useful for chemicals that make small contributions to the mixture, which are normally hard to detect. The UDRC algorithm is easily reconfigurable to include new library entries and optional preferential threat searches in the presence of predetermined threat indicators [22].

The algorithm has been demonstrated for fingerprinting chemical mixtures using a set of reference spectra. The algorithm successfully managed to detect weak Raman scattering chemicals with concentrations below 10%, which are conventionally challenging on some hand-held Raman systems. The running time of the algorithm is of the order of one second using a single core of a desktop computer.

The spectral selection technique has the potential to accommodate extra criteria to increase accuracy or sensitivity. One such example is preferential spectral decomposition, when the existence of one chemical influences the sensitivity to an-

seconds.

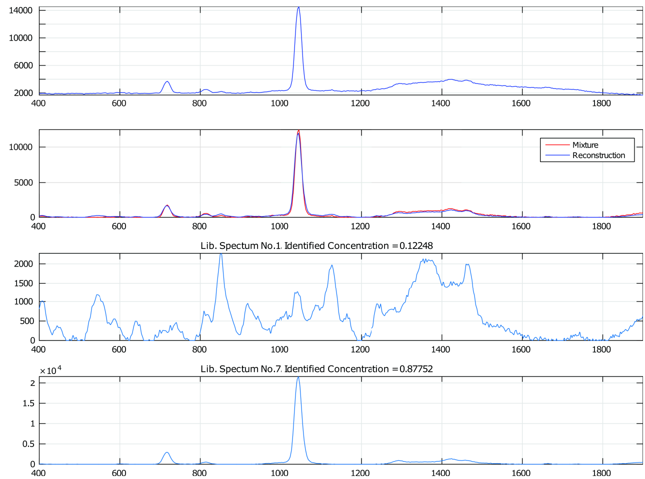

Figure 2.6: Sparse Raman spectral decomposition for fingerprinting and quantification. Panels indicate (from top): original mixture; reconstructed spectrum from inferred mixture; two library components making up the inferred mixture.

other (hard to detect) chemical. This is useful in detection of composite explosives or mixed toxic chemicals.

Data challenge and enabling contracts: Raman spectral decomposition

At the signal separation theme meeting in 2013, Dstl presented a Raman spectral decomposition challenge. This solicited novel, simple, approaches to identify whether the current limits of established Raman mixture analysis were an accurate reflection of the spectral information present. Limitations placed on responses included:

- to be able to identify the components of a series of mixtures (not all components were present in the library),
- be easily reconfigurable to cope with new libraries,
- not to rely on time-consuming training algorithms,

- to be technology agnostic with flexibility to adapt for more complex scenarios in future iterations.

Two approaches were submitted to the challenge. The winning contribution was based on convex optimisation [23]. A simple low-order polynomial model for baseline correction, excluding peaks, and an innovative method for the detection of an unknown spectrum was part of the winning approach. The approach correctly identified the mixture components at all concentrations, demonstrated that there is sufficient signal at low concentrations to permit detection, and detected the presence of a component which was not in the reference library. Following the success of the data challenge, the approach was further developed under three enabling contracts.

1. A preliminary investigation of Raman spectral deconvolution with spectra from different instruments confirmed performance against a range of sources and expanded on the results from the initial challenge. The additional data prompted characterisation of baseline correction. Computational complexity reduction was another aim of this study, to provide a proof of concept demonstration that this approach could be used on hand-held devices.

2. The focus of this work was on detecting even lower concentration components for specific chemicals where a cueing chemical is present to indicate the presence of the target chemical. In addition, adaptation of previously-developed code into C was undertaken to permit a proof of concept implementation onto a prototype Raman spectrometer.

3. The focus of this stage was a scoping study focussing on different spectral shifts in a subset of Raman mixtures which can impede spectral matching. Supporting work was also undertaken in identifying computationally efficient approaches for baseline correction.

Further development of sparse methods for Raman spectral decomposition

A fast decomposition algorithm with implementations in C and Java was developed under the UDRC and associated enabling contracts. It was tested with small to medium sized libraries (fewer than 150 spectra) of sufficient size to identify whether a threat material is present. The algorithm was tested intensively with synthetically generated mixtures and a subset of representative real-world mixtures. Adaptations to this fast decomposition algorithm have been made. They are currently only available as research code but include the following.

- Preferential spectral deconvolution: in the presence of a trigger chemical, the associated threat spectrum has increased weight. The modified algorithm has higher true positive and smaller false negative rates for low concentration spectral components.
- Light sparse decomposition: removes the low-order polynomials associated with fluorescence before spectral deconvolution. While this may seem a simple approach, it performs in a similar manner to complicated baseline correction methods, but at a fraction of the computational cost.
- Modified non-linear spectral deconvolution: accounts for spectral shifts associated with shifted mixture components. The method is limited to single peak shifts at present.

2.2 Signal separation and broadband beamforming

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In this section the application of sparse signal separation techniques is considered in the context of defence-related underwater acoustics. The problem addressed here is that of using passive sensor arrays to detect and localise the direction of moving targets. In passive systems one or more receiving sensors are used to record ambient signals. Unlike active systems there is no control over the strength of the received signal from objects or clutter. There is potential for high levels of noise in the recorded signal. In beamforming and source separation, the task is to estimate the signal of interest, and the direction of arrival (DOA) in the presence of interfering clutter and noise with the aid of an array of sensors. These sensors are located at different spatial positions and sample the wave propagating through space.

The collected spatial samples are then processed to attenuate or null out the interfering signals and extract the target signal. The specific spatial response of the array system can therefore be conceived of as beams pointing to the desired signals and nulls towards the interfering ones. In order to achieve this spatial response a weighted combination of each sensor in the array is used. Finding the optimal weight coefficients to produce such an effect is the principal business of beamforming. One of the goals of tailoring an array response is the reduction in the level of the so-called *sidelobes* of the main beam. Sidelobes are artefacts of the beamforming process where the array retains sensitivity to targets and interference outside of the main beam. It is usual to require or desire small sidelobes so that the signal of interest, in the main beam, is distinguished from spatially separated targets, interferers and clutter

The beams used in beamforming depend not only on the array's geometry (the aperture) but also on the frequency of operation. Sensitivity to a wide range of frequencies is a desirable property in many defence-relevant scenarios. Targets, especially faint ones, may exhibit a complicated response and their detection and characterisation, or their distinction from clutter, may hinge on the ability to observe them over a broad frequency baseline. If array signals exceed a certain fractional bandwidth, however, or span more than one octave, then the pointing direction of the narrowband beams changes with frequency. This disrupts the look direction, and requires the explicit enactment of broadband beamforming approaches which account for the delays with which signals illuminate different array elements. This significantly increases the dimensionality of processing, thereby increasing the computational complexity, and potentially negatively affects the numerical stability of the solution. Dedicated, numerically efficient and robust approaches are therefore crucial for beamforming in broadband array signals.

2.2.1 Bayesian broadband beamforming in sonar

The UDRC conceived a solution based on the adaptive sparse sequential Bayesian approach originally proposed by Mecklenbräuker

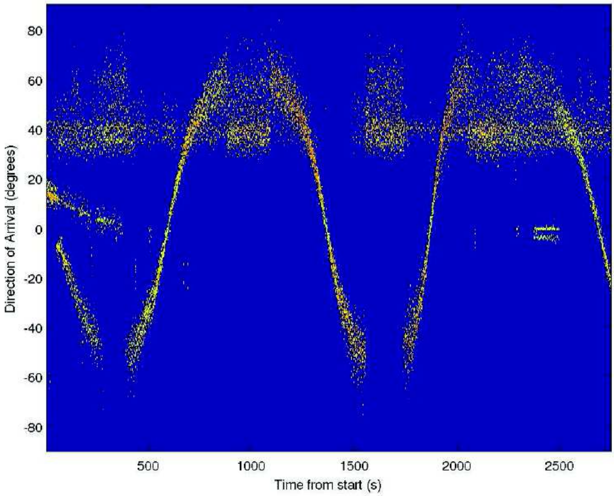

Figure 2.7: Direction of arrival of sources for tracks 1 to 5 of the Portland 03 dataset observed at $125 - 185\text{Hz}$. The y-axis is DOA, positive up and negative down ranging from $-90°$ to $90°$. The x-axis is time (s).

et al. [24] for underwater source separation and tracking. The goal in this work was to de-noise, separate and track the DOA of moving acoustic sources. This was done by extending the classic method to a sequential maximum a-posteriori (MAP) estimate of the signal over time. A sparsity constraint was enforced through the use of a sensible prior at each time step. An adaptively-weighted cost function was sequentially minimised using the new measurement received at each time step. This gave a sparse output from the DOA estimation algorithm, and reduced the amount of noise in the final DOA estimate.

UDRC researchers evaluated their approach on a dataset supplied by Dstl (known as Portland 03). These data were collected in Portland harbour off the South coast of England in December 2003. The recordings were made with two parallel 32 element hydrophone arrays. The target source is a small fishing vessel which travels past the arrays in a number of ways (including parallel and perpendicular paths). The vessel's engines were turned off between transits giving portions of the data where no target acoustic source is present.

Figure 2.7 shows results of the UDRC method on broadband Portland 03 data covering 125Hz to 185Hz. It can be seen that the DOA of the target acoustic source is accurately localised and tracked through most of the sequence. There is a stationary noise source in the data at approximately $+40°$ and at a number of places in the sequence this source is tracked. This is always (at approximately 300s, 1000s, 1600s and 2200s) when the engine of the target vessel was turned off. It can also be seen that the angular resolution of the DOA estimate is most accurate when the target source is directly broadside of the array in the middle of each track.

As a result of this work several software toolboxes have been generated and made available to the community:

1. *Sparse analysis model based dictionary learning algorithms* (a Matlab toolbox) [25]
2. *Sparse analysis model based multiplicative noise removal* (a Matlab toolbox) [26]
3. *Sparse sequential Bayesian algorithms for DOA estimation* (a Matlab toolbox and demo)

The work undertaken by the UDRC has been conducted on both simulated data and the Portland 03 dataset. Further work will demonstrate how this method generalises to different situations. A further research direction is the modification of the sparse optimisation algorithm to improve DOA estimation whilst keeping the number of active sensors to a minimum. This is desirable in cases where sensors are unreliable, or their cost to operate becomes burdensome.

2.2.2 Signal separation for large sonar arrays

As a result of the UDRC work the researchers participated in a TTCP[5] workshop on signal processing for large sonar arrays in 2014, organised by Dstl. The objectives of the workshop were to present technical papers on joint research, to discuss progress and identify topics for potential future collaboration. The UDRC researchers gave an introduction to broadband signal separation methods based on polynomial matrix decompositions (see §6.1). As an alternative to adaptive beamforming, it was proposed that broadband signal separation techniques could be used to separate out different signals and then apply a *Capon beamformer* – which is optimal for a single source.

A subsequent meeting was convened later in 2014 with attendees from the UDRC, Dstl and Thales Underwater Systems (TUS). The main purpose was to identify technical approaches which could be used to optimise the performance of large sonar arrays which may contain many individual sensors (e.g. figure 2.8). A key challenge is to develop approaches that implement adaptive beamforming across the full sensor array in order to suppress correlated sources of noise. To achieve this, low-complexity techniques and data reduction methods are required which can maintain optimal performance while overcoming the processing challenges inherent in systems with such a large number of sensors. Operator workload is also a significant challenge in managing the information from large sonar arrays. Broadband signal separation techniques offer a radically different approach for separating signals which could potentially reduce workload if different signals can be reliably separated.

The meeting covered challenges, current methods and broached a number of radical approaches. Outcomes from the meeting were:

[5]The Technical Cooperation Program is a joint Australia, Canada, New Zealand, UK and US initiative to foster international collaboration on mutually-beneficial research in the defence sphere.

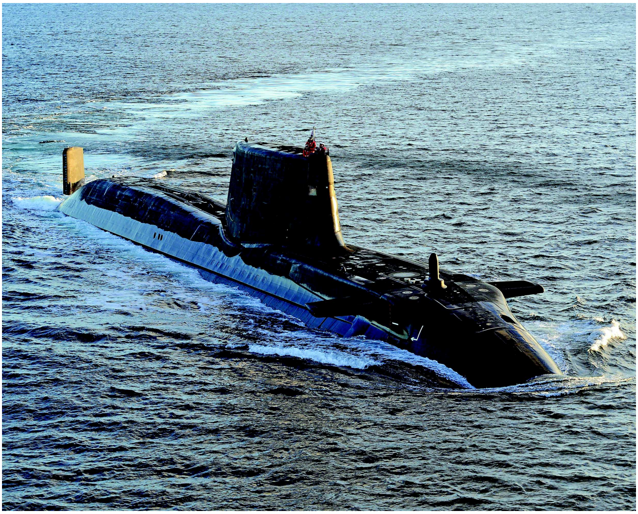

Figure 2.8: Starboard view of HMS Ambush, an Astute Class submarine, underway during sea trials. The flank array is forward of the fin (or sail) below the bow plane.

- Dstl made available passive array data to the UDRC researchers.
- TUS supplied a passive array simulator, via Dstl, to the researchers for algorithmic test and development.
- Strathclyde University and TUS explored ways of working together to advance this technology.

The scope and timescales for this final item were the subject of a meeting at TUS, attended by Dstl and Strathclyde in 2016. These included potential internships, secondments to TUS or jointly-sponsored PhD schemes, and continuing joint applied research [27]. As a result, UDRC researchers, with the support of Dstl and TUS, sought and successfully secured a John Anderson Research Award from Strathclyde University. This is a prestigious PhD scheme, which runs for four years from October 2017. The subject is broadband signal separation techniques and it includes an internship at TUS beginning in March 2018.

2.2.3 Maritime Collaborative Enterprise

In 2015 UDRC researchers at the University of Surrey, partnering with Atlas Elektronik UK, won funding from the Maritime Collaborative Enterprise[6] (MarCE). The aim of the project was to investigate the use of sparsity-based methods for sonar array optimisation, derived from the source separation and broadband beamforming work being undertaken by the UDRC.

A convex sparse optimisation method was used to reduce the number of sensors in the array while maintaining performance, and also to demonstrate the ability to control sidelobe level. The work was completed between September 2015 and June 2016 and a report and a software package were delivered. The key findings of the study were that in order to maintain a response whilst reducing the number of sensors, the convex optimisation solution concentrates the active sensors in the centre of the array with a few active sensors towards either end of the array. While this retains a narrow main beam it can cause significant grating lobes as the number of sensors is reduced. In the case of an unshaded array (where all array elements are equally responsive), the sparse configuration pattern concentrates errors in large sidelobes at -90 and 90 degrees. Additionally, the UDRC researchers demonstrated that sidelobe levels can be controlled by adding constraints to the optimisation. In this particular case a decrease in the size of the first two sidelobes is achieved. This could be extended in principle, however, to control the array response in an arbitrary direction.

[6]The Maritime Collaborative Enterprise was a community of interest, led by BAE Systems, which managed placement and execution of research tasks on behalf of Dstl, relevant to MOD maritime stakeholders.

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Chapter 3

Multiple sensor processing

The UDRC has developed novel signal processing methods for multiple sensor systems, including spatially distributed and multiple-input, multiple-output networks. The applications encompass radar, sonar and communication networks that, as well as being spatially disparate, may also support distributed processing. The UDRC methods work with active and passive sensors improving performance and robustness and are suitable for use in a cluttered networked battlespace.

3.1 MIMO sonar systems for underwater acoustic sensing

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Multiple-Input Multiple-Output (MIMO) refers to a system of several transmitters and several receivers. A MIMO system

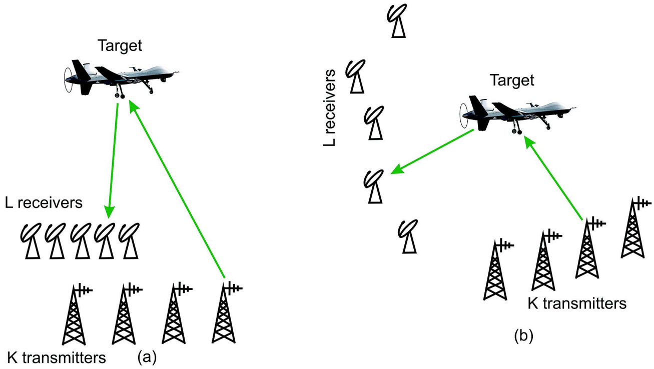

Figure 3.1: Examples of (a) co-located MIMO and (b) spatially distributed MIMO systems

is distinguished from a multi-static system (merely meaning that transmitters and receivers are not in the same place) by its ability to simultaneously transmit and jointly process all received signals. There are broadly two varieties of MIMO system depending on the geometry of the antennas: co-located MIMO where transmitters and receivers are sited near each other (figure 3.1a), and spatially distributed MIMO (figure 3.1b). This work focusses on the latter and describes the properties and possible applications for large distributed MIMO sonar systems. MIMO systems have been investigated over the past two decades in wireless communications [1], before attracting the interest of the radar community [2]. Studies of MIMO radar have highlighted the many advantages of these systems, such as diversity gain for target detection, Doppler estimation and improved resolution for target localisation. It is only recently that the sonar community has started to investigate MIMO systems. The UDRC has demonstrated that large spatially distributed MIMO sonar systems have advantages in terms of automatic target recognition (ATR) and super-resolution for underwater applications.

3.1.1 Fundamental properties of MIMO systems

The theoretical study of MIMO systems cannot be approached by conventional methods such as beamforming theory. The location of the K transmitters and L receivers introduces $K \times L$ unknowns into the problem and the deterministic approach in beamforming cannot derive the most interesting characteristics or properties of such a system. Instead, UDRC researchers developed an entirely generic new statistical framework to study large MIMO systems. Two assumptions underpin the theory of spatially-distributed MIMO systems.

- Independent views: this assumption is the definition, in statistical terms, of the term *spatially distributed*. It simply means that the antennas are sufficiently far apart from each other that each pair (one transmit and one receive) are statistically independent from all other pairs. This assumption and its implications have been used by UDRC researchers as tools to design practical MIMO systems.
- Orthogonal waveforms: this assumption is common in MIMO theory. Orthogonality imposes a constraint on the transmitted waveforms, thus ensuring that, at the receiver side, the components from different transmitters can be isolated. Strictly, this hypothesis is false but orthogonality can be approximated reasonably well. The UDRC has proposed a solution to this problem suited to large MIMO sonar systems (§3.1.5).

3.1.2 Target recognition properties

Thanks to the statistical framework developed under the UDRC, it has been shown that the response of a target contained within one resolution cell is equivalent to a random variable [3]. The independent views assumption ensures that all the observations of the target (from each MIMO pair) are statistically independent. It can thus be shown that, with one MIMO snapshot (i.e. $K \times L$ observations) and as long as the MIMO system is large enough, it is possible to estimate the distribution of classification probabilities (the probability density function: PDF) of the observed target. More formally, this concept can be integrated into a Bayesian framework as described in [4], and it is possible to compute the probability of a target belonging to a given class.

Even at low signal-to-noise ratio (SNR) and with relatively few views, the UDRC work shows that a MIMO system shows excellent target recognition. Furthermore, thanks to the large number of independent observations, large spatially distributed MIMO systems have ATR capability built into their core mechanics. It is important to note that the MIMO ATR capability relies only on fundamental target properties and not on any prior assumptions.

3.1.3 Super-resolution of MIMO systems

The second major MIMO property emerges when investigating how to fuse the multiple views acquired by a large MIMO system. One might expect the classical result that the average intensity function of independent observations converges towards a Rayleigh distribution. Rigorous calculations show, however, that the average intensity probability function collapses into a Dirac function [5]. Figure 3.2a illustrates this point graphically: as the number of independent observations approaches infinity, the probability density function of the intensity average converges towards a Dirac distribution. The physical consequences of this fundamental result are profound. As the number of independent observations increases, the MIMO system de-correlates the contribution of every scatterer within one resolution cell. MIMO systems then overcome the limitation of coherent systems and, with enough independent views, large MIMO systems resolve the speckle within each resolution cell. Super-resolution can therefore be achieved using large MIMO

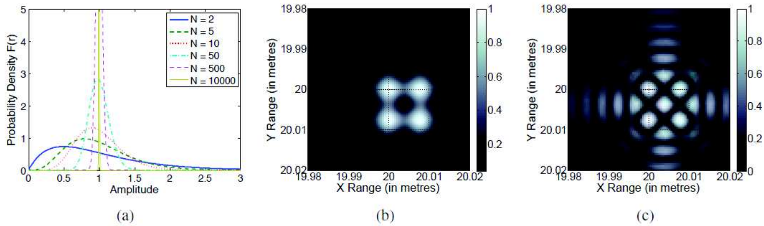

Figure 3.2: (a) Convergence of the average intensity function to a Dirac function; (b) normalised MIMO image of a target with 4 scattering points; (c) normalised CSAS image of the same target. The latter method uses conventional processing techniques which cannot resolve the scattering points unambiguously.

systems.

To illustrate this point, figure 3.2b shows a MIMO image created with a variant of the UDRC algorithm [4]. The target has 4 scatterers located at a vertex of a square with size $\lambda/2$ (where λ represents the wavelength). As the figure illustrates, the 4 scatterers are resolved and the geometry of the target is recovered. To compare, figure 3.2c plots a circular synthetic aperture sonar (CSAS) image of the same target. CSAS maximises the virtual antenna aperture and provides the highest resolution possible using synthetic antenna systems [6]. The CSAS processing is not able to differentiate the 4 scatterers. The coherent processing of the independent observations provided by a large MIMO sonar system can thereby surpass the resolution of current sonar imaging systems.

3.1.4 Unlocking MIMO properties

This section further examines the two main assumptions made previously; of independent views and orthogonal waveforms. Far from being a burden, interrogating these assumptions leads to the tools necessary to design and build practical MIMO sonar systems.

Independent views

Many sonar arrays exhibit a target response which is very sensitive to view angle [7]. This observation gives the first indication that multiple independent views across a large MIMO system might be achievable. In order to ensure statistical independence of all views, it is necessary to build mathematical tools to measure independence. The independent views problem is in essence the inverse problem of the signal correlation problem. Correlation is usually calculated using the Pearson product-moment correlation coefficient [8]. This correlation coefficient has a number of flaws, however. It only measures linear correlations between two random variables, it has been designed for normal distributions, and it is not a real measure of independence. In [4], UDRC researchers introduced the *MIMO intercorrelation distance matrix*, based on the distance correlation to overcome these problems. This new distance matrix can assess the level of independence between MIMO pairs as a function of their geometry, which is essential when designing large MIMO sonar systems.

Orthogonal waveforms

Mathematically, it is straightforward to prove that two finite signals can never be entirely orthogonal. Several strategies have been developed to find an approximation to the orthogonal waveform problem, including Time Division Multiple Access (TDMA), Frequency Division Multiple Access (FDMA) or Code Division Multiple Access (CDMA). The relatively slow speed of sound in water makes the use of TDMA difficult for large MIMO systems. Bandwidth is a scarce resource in sonar systems and so FDMA is also not a viable option.

In [9], [10], UDRC researchers proposed a novel CDMA waveform family: the *Interlaced Micro-Chirp Series* (IMCS), which fits the requirement for large MIMO sonar systems. The IMCS combines the coverage of the full frequency band for each waveform while having very low cross-correlation functions and minimal sidelobes. The signal phase varies slowly and is suitable for the piezo-electric transducers found in sonar systems.

3.1.5 Applications of MIMO sonar systems

Harbour surveillance

The new MIMO paradigm developed by the UDRC leads naturally to MIMO systems for underwater surveillance. Presently, harbour surveillance is mainly performed using radar systems, but the potential for heterogeneous threats, including divers and autonomous underwater vehicles (AUVs), requires underwater surveillance as well as a surface surveillance. In [11], UDRC researchers developed a MIMO simulator capable of handling complex, heavily cluttered and very shallow water environments similar to the ones that are found in harbours. Figure 3.3a shows an example scenario. The simulator is physics-based and can accurately model seabed reverberation (see figure 3.3b for the intensity response of one MIMO pair), or multipath propagation.

The number of detections generated by a MIMO sonar system can be large, preventing direct interpretation by an operator. Algorithms to correlate the data in space and time can be used to facilitate understanding of the scene. Due to the complex nature of the harbour protection problem, robust and reliable estimators are needed. In [12], UDRC researchers, including those working on novel tracking and sensor management methods, proposed a new multi-target tracker based on the Hypothesised filter for Independent Stochastic Populations (HISP; itself a UDRC-developed method, see §4.2.3). This filter is capable of performing target classification based on the behaviour of different targets. Fish are assumed to swim in a somewhat random fashion while boats or AUVs move more directly. Figure 3.3c plots the result of the HISP tracker and classifier. The filter tracked the objects of interest and classi-

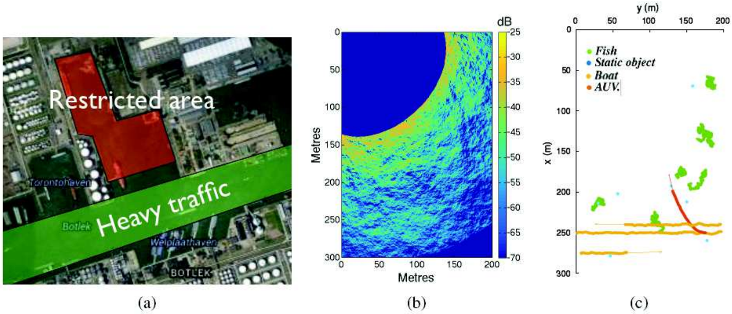

Figure 3.3: (a) Harbour surveillance scenario in a realistic environment; (b) a synthetic sea floor MIMO response generated by the UDRC simulator; (c) position, trajectory, velocity and target classification of the HISP-filter tracks (colour code: black = false alarm, green = fish, blue = static object, yellow = boat, orange = AUV)

fied them correctly. As objects are distinguished by the filter, trajectories are also naturally available, so that the AUV (the threat in this scenario) can be seen to have been dropped by the second boat [12].

New strategies for anti-submarine warfare

Traditional active sonar systems are pulsed active sonar (PAS). With low duty cycles (typically 1% or lower), the receivers are usually switched off during transmission to avoid the direct-path energy which can saturate the system. Recently, continuous active sonar (CAS) systems have attracted a lot of interest, especially in the anti-submarine warfare (ASW) community. Using IMCS pulses developed under the UDRC [13] in an ASW scenario offers two main advantages over current methods:

1. Decreased pulse repetition interval (PRI): several orthogonal pulses can be transmitted during one PAS PRI. If the tracking is not continuous as in CAS, the potential

hit on a target is multiplied by the number of pulses sent during one PAS PRI period.

2. Multiple transmitters: several transmitters sending orthogonal pulses can be used in such scenarios, increasing view diversity and overall coverage.

In many respects, a MIMO system is much more than the sum of its parts. By jointly and coherently processing all the received signals, the UDRC has shown that large MIMO systems have inherent capabilities such as ATR and super-resolution. By multiplying the number of transmitters and receivers, MIMO systems also offer flexibility in terms of system design and signal processing. The large number of degrees of freedom of such systems can be used creatively to provide practical and innovative solutions for problems as diverse as harbour protection or anti-submarine warfare. It is also worth mentioning that the MIMO framework presented here will become increasingly relevant as the current trend in underwater robotics for multi-vehicle collaboration increases. Sensing using MIMO technology will then bring access to a deeper understanding of the environment and facilitate autonomy for underwater robotics.

3.2 MIMO and distributed radar sensing

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Inspired by the benefits gained from MIMO implementations in communications, MIMO radar systems have attracted research interest due to the promise of significant performance increases when compared with phased array radars. As in the previous section, MIMO radar systems are classified into two main categories: co-located or distributed, depending on the spatial distribution of their antennas. As a new concept, distributed sensing poses many challenges associated with embodying the technology. These include designing the waveform to optimise spectrum allocation and reduce complexity. Furthermore, existing challenges in traditional radar systems can be re-defined to take advantage of the extra degrees of freedom provided by MIMO systems (such as in ATR). Three particular challenges in distributed sensing have been addressed by the UDRC work: waveform diversity and spectrum sharing, robust ATR and low-SWAP requirements.

MIMO systems are characterised by having multiple transmitting and receiving antennae, with transmitters acting simultaneously. A graphical illustration of a MIMO radar system composed of three transmitters and two receivers is shown in figure 3.4. Such systems require the waveform of each transmitter to be sufficiently different so that the receivers are able to separate their respective pulses, (referred to as waveform diversity: WD). While the problem of WD can be resolved in theory by applying modulation schemes such as orthogonal frequency-division multiplexing (OFDM), the limited available bandwidth has to be separated for each transmitter. This can lead to drawbacks such as range resolution degradation. A similar problem to that of WD can arise when communication and radar systems are operating in the same band. This problem is more commonly known as spectrum sharing and, similarly to WD, can lead to performance degradation. The challenge is to design waveforms which are sufficiently diverse to use in MIMO systems, without sacrificing radar performance.

Target recognition is an ever-present concern in radar system design. In the past, recognition and classification of targets was done manually by trained operators. Today more advanced systems are able to perform some of these operations automatically. There is a need to improve these algorithms to provide

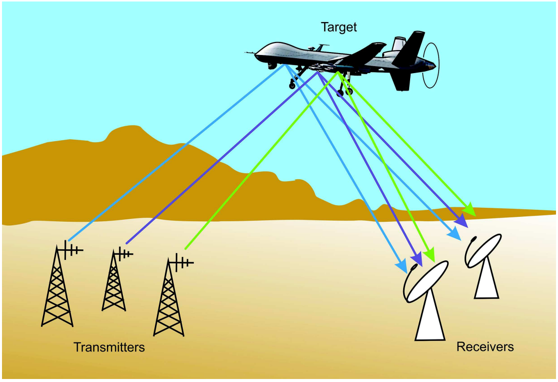


Figure 3.4: Illustration of a 3×2 MIMO radar system with diverse waveforms

better accuracy and robustness for more complex targets in rapidly changing and diverse environments.

The distance and relative velocity of a target can be found using the echo of the illuminated target. Radial motion estimates are acquired from shifts in frequency (i.e. the Doppler effect). While the main Doppler shift is associated with the bulk movement of the object, secondary motions such as rotations and internal movements will introduce so-called *micro-Doppler* on the returns. As micro-Doppler signatures can reveal the internal structure of an object, they have the potential to be discriminatory classifiers. Development of well-designed algorithms of this type is very challenging, however, due to the dependence of the signal on the phase and scale of the motion.

In contrast to some sensing systems, such as those based on optical sensors, radar is able to operate in a wide range of light and weather conditions. This has made it popular in numerous military and commercial applications, and lower SWAP requirements continue to drive the technology. The low SWAP challenge is correlated with the spectrum sharing and ATR problems. A conventional solution for a system performing both communication and radar operations is to be equipped with two separate sub-systems; one for each. A better option is to build a single system to perform both operations and so ensure lower SWAP. Ensuring high robustness in ATR can lead to computational heavy algorithms, however, and implementation of these poses challenges for low-SWAP requirements.

3.2.1 Practical advantages of MIMO radar

The UDRC researchers have developed a class of waveforms which are sufficiently diverse to be used in MIMO systems. These waveforms require only low-cost, low-SWAP hardware, such as software-defined radios (SDRs), and as such can be realised on low-cost MIMO systems with many nodes, possibly mounted on unmanned aerial vehicles (UAVs). A large MIMO network, and the spatial diversity it brings, can aid detection of low-observable objects, as well as improve the detection, classification and tracking of other targets in a larger field of regard. As well as supporting MIMO systems, the same waveforms can be used to encode communications, making radars multi-use.

UDRC researchers developed a classification algorithm which is able to distinguish between walking and running pedestrians. This scenario is challenging for a classification algorithm due to the complex bulk and limb motion, so is a good test of performance. As well as having utility in the automotive industry, this classification technique has been further developed and demonstrated in the defence sphere by application to helicopter classification [14] and ballistic missile detection and classification, in work funded by the Centre for Defence Enterprise[1] (CDE) [15].

[1] In 2016 the Centre for Defence Enterprise became the Defence and Security Accelerator

3.2.2 Fractional Fourier Transform based waveform diversity and communicating radar

To address the challenge of WD in radar systems, a novel waveform design based on the Fractional Fourier Transform (FrFT) was developed. While a complete definition of the FrFT is outside of the scope of this work, in essence FrFT can encode input signals into different chirp-like sub-carriers. These sub-carriers occupy different bandwidth slots in different time intervals, following a linear trend. Properly designed, the sub-carriers can be distinguished from one another even if they overlap in both time and frequency. This allows for flexible waveform design as any signal can be encoded in the sub-carriers. In the UDRC work information-carrying signals are employed to enable the dual functionality of the same system.

For a MIMO system, a different sub-carrier can be assigned to each transmitter. This allows each receiver to distinguish the source of each pulse and apply appropriate processing, even in cases where transmitters are active simultaneously. Alternatively, if only one transmitter is employed, then sub-carriers can be combined to carry more information in one waveform. This is also called the communicating radar (Co-Radar) waveform. An illustration of the synthesis of a Co-Radar waveform with four sub-carriers is given in figure 3.5. The time-frequency profiles of 4 information-containing signals, S_1, S_2, S_3 and S_4, are illustrated in the upper part of the figure. Those signals are used as inputs to FrFTs of different orders (described as $\mathcal{F}$ blocks), to generate sub-carriers of different time-frequency occupancy, S_1', S_2', S_3' and S_4' respectively (lower part of figure). At this stage, these sub-carriers can be used independently by different transmitters or be combined to form a Co-Radar waveform if one transmitter is operating.

The prototype of the FrFT Co-Radar system consists of a mono-static radar that generates the FrFT waveforms, sends the pulses and performs basic radar tasks, and a separate com-

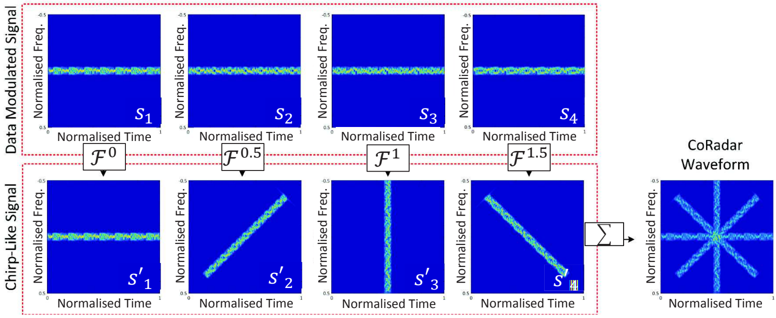
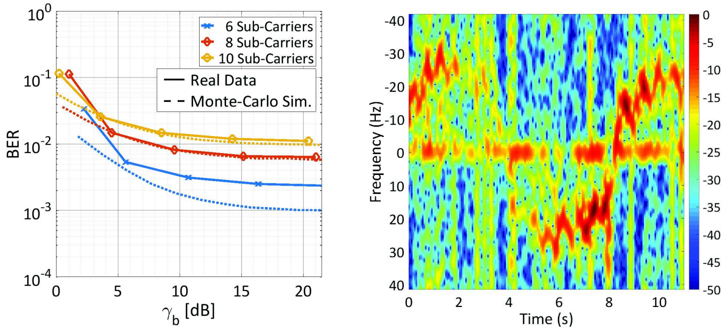


Figure 3.5: Multiplexing of four data modulated signals using FrFTs of different orders to form a Co-Radar waveform

munication receiver that demodulates the pulses [16]. The entire system is implemented in an SDR, to allow for real-time novel waveform design and processing. Figure 3.6a shows the communication performance of the FrFT Co-Radar in different configurations evaluated on real data (solid lines), and compared to simulated data (dashed lines). The system is able to achieve good communication performance, in agreement with the simulated results. Figure 3.6b shows the spectrogram of a walking person generated from radar returns using Co-Radar waveforms of 8 sub-carriers. When the person is moving towards and away from the radar, negative and positive Doppler shifts are clearly evident.

3.2.3 Micro-Doppler based ATR

As has been seen above, observations of the micro-Doppler signature of a target can provide discriminative characteristics which can lead to reliable classification of the target. As an example consider the returns from a person walking and running. Due to the different motion of the limbs, each target will introduce distinct frequency shifts in the returned signal, making the classification of two similar targets possible. These differ-

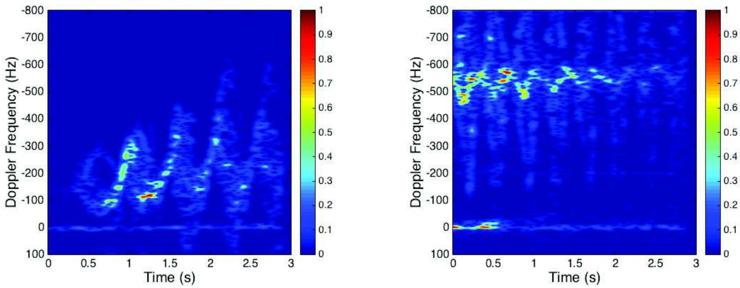


(a) Communication (b) Radar

Figure 3.6: (a) Communication performance in terms of bit error rate (BER), for varying energy per bit to noise power spectral density γ_b and for different number of sub-carriers. Lower numbers indicate better performance. (b) Spectrogram obtained from FrFT Co-Radar pulses with eight sub-carriers: person walking towards the radar approximately between $4-8$ seconds, and away from it between $0-4$ seconds and $8-11$ seconds.

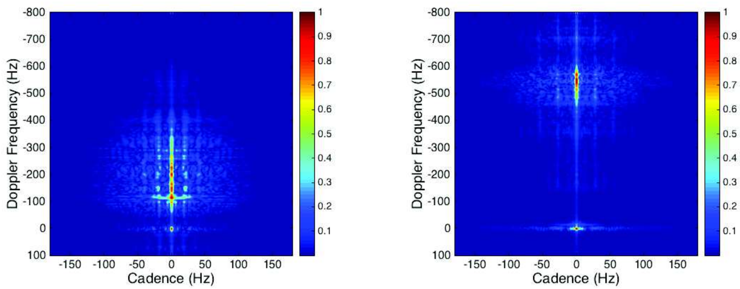
ent frequency shifts are shown clearly by the spectrograms of a walking and running individual in figure 3.7.

The problem with using the spectrogram as an input to the classifier is that if the target is captured at a different phase of their motion, the time-frequency profile will not be the same. To mitigate this issue, the frequency-verses-time spectrogram can be Fourier transformed in time to provide a frequency recurrence profile. This is referred to as a cadence velocity diagram (CVD), and is invariant to the phase of the pedestrian's motion. Figure 3.8 shows CVDs generated from the two spectrograms in figure 3.7. Additionally, after the CVD is generated, feature extraction is undertaken using Krawtchouk (Kr) moments. The Kr moments are a set of moments formed using Krawtchouk polynomials and are widely used for image processing. Kr moments are scale, rotation and translation invariant, making them very attractive for feature extraction [17].



(a) Walking (b) Running

Figure 3.7: Normalised spectrograms of an individual (a) walking and (b) running, from a 24GHz continuous wave (CW) radar



(a) Walking (b) Running

Figure 3.8: Normalised cadence velocity diagram of an individual (a) walking and (b) running

Moreover, the proposed technique has low computational cost, and so has the benefit of allowing real-time implementation in low SWAP hardware [17]. A similar concept has been applied by UDRC researchers for helicopter and ballistic missile classification [14], [15].

3.2.4 Further exploitation of algorithms for MIMO radar

Having successfully developed a proof of concept demonstrator for the Co-Radar system, the current direction is toward its implementation in automotive platforms. In particular, the Co-Radar waveform is to be extended to a continuous wave design to allow higher data rates and to cope with the challenges of fast changing channels.

Future plans regarding the micro-Doppler ATR include its commercialisation and application in autonomous systems for accident prevention, autonomous systems for pedestrian monitoring and intrusion detection in security systems. To enable adaptation to this variety of applications, the implementation of techniques such as unsupervised machine learning will be investigated.

The research undertaken by the UDRC has been used as a basis to secure the additional following funding:

- *Persistent surveillance from the air*: UDRC researchers at Strathclyde University won funding in October 2015 to develop their communicating radar concept for application to medium altitude long endurance (MALE) UAVs. The project was part of the persistent surveillance from the air CDE call. It addressed the issue of spectrum sharing between communication and radar while conforming to the low-SWAP requirements of MALEs. The UDRC researchers presented the final demonstration of their work at a 'marketplace' event in London in April 2016. This project drew on fundamental research in the UDRC, and both informed and collaborated with phase 1 follow-on work undertaken by University College London on cognitive radar. See [18] for a video description of the innovation and a description of its application to the problem as defined in the CDE call.

- *Defence against airborne threats*: This project, answering a CDE call from the UK Missile Defence Centre (MDC), sought to demonstrate the potential of exploiting radar micro-Doppler signatures in order to provide discrimination of ballistic missiles from clutter. It addressed the need to develop robust, low complexity techniques for classification in missile defence systems. The project led to a practical instance of the micro-Doppler based classifier. The outputs were fed back into the MDC (see §7.3.1 for details of next steps). In all, Strathclyde University now have four ongoing contracts with MDC to provide consultancy on various aspects of BMD research.

- *Joint communication-radar operations in automotive applications* An industry-funded project on the extension of the Co-Radar concept to automotive applications. The funds fully support a PhD studentship at Strathclyde University and are designed to investigate the WD and spectrum sharing challenges in modern intelligent transport systems. The project will extend the existing FrFT based communication-radar scheme to cope with the challenges and requirements associated with automotive systems.

- *GNSS-based UAV monitoring system using passive observations (GUAPO)* Following the UDRC researchers' victory at the European Satellite Navigation Competition (see §7.1), funding was secured for the development of a GNSS-based UAV monitoring system. The project looked at developing low-cost, low SWAP and easy to deploy UAV monitoring solutions. This has been augmented by funding from the EPSRC Impact Acceleration Account and UK Satellite Applications Catapult. The aim for the current stage of funding is a preliminary theoretical and experimental analysis, de-risking, and business development for the GNSS based UAV monitoring technology. It will report experimental results and develop a business plan to take the technology forward.

- *Simulation of micro-Doppler signatures.* Two projects are ongoing, funded by a consumer electronics manufacturer, to develop the micro-Doppler signature models to extract target kinematic models.

3.3 Distributed multi-sensor processing

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Many military applications rely on multiple networked sensors (e.g. figure 3.9). They can increase sensing coverage and accuracy, and enhance communication potential. Typically in real defence scenarios they are sparse, low-bandwidth, heterogeneous combinations of complex data sources. In order to operate robustly in a changing environment, these networks must be scalable, fault-tolerant and flexible. The UDRC has developed sensor network concepts that mitigate the need for a specific fusion centre to provide robustness and flexibility in changing environments and minimise the communication overhead.

With multiple sensors and one fusion centre the major choices for detection are (i) global, where all the data is fused; (ii) distributed, where the decision metrics are fused. Alternatively, in the absence of a fusion centre, distributed and decentralised detection (DDD) can be undertaken, where each node makes a decision based on its own data and side information from neighbouring sensors. With the latter, what might initially be a poor detection decision at a particular node will improve with communication opportunities and as information propagates back

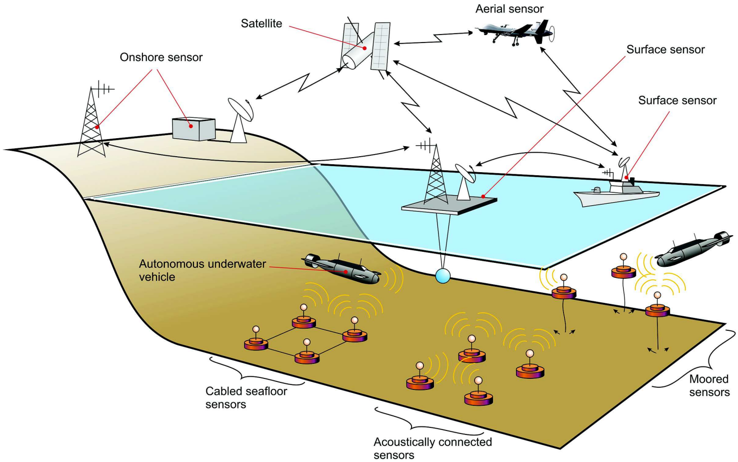

Figure 3.9: An example of a distributed sensor network (after [19] and [20])

and forward across the network. This also has military benefits such as reduced reliance on critical nodes, reduced bandwidth and better scalability when adding nodes to the network.

The UDRC team has developed both distributed and centralised algorithms for processing multiple sensor data streams. The distributed algorithms aim to trade-off the need for a single, potentially fragile, processing centre against losses in accuracy and latency. As a counterpoint, centralised processing algorithms capable of scaling with the number of sensors for cases in which it is feasible to collect the network-wide data at a fusion centre have also been investigated. Integral to each approach is a consideration of the capabilities and limitations of the communication links between the sensors in the network. The team adopted a network-centric approach for distributed multi-sensor processing and linked it to the sparse processing and sensor management aspects of the UDRC.

3.3.1 Networks of sensors in defence systems

This work has application in any of the scenarios in which the military makes use of networked sensors. The theory is therefore very valuable as an underpinning technology which can be brought to bear in a number of applications. The UDRC algorithms provide new means for automatic calibration in networks of sensors, which has advantages in terms of scalability and the ability to cope with realistic uncertainties. One particularly useful application is sensor localisation in GPS-denied environments. The level of abstraction facilitates use in a wide range of sensing modalities (e.g. radar, sonar, lidar). During the UDRC phase 2 three specific examples have focussed the researchers' output on practical implementations.

Sonobuoys for anti-submarine warfare

Sonobuoys are unattended underwater sensors, usually anchored to the seabed and operating at varying depths in the water column. Such sensors suffer from significant drift in all dimensions due to changes in underwater conditions. UDRC researchers adapted their methods for registration of passive sensors and used this problem as an early motivating scenario. The output was used to inform Dstl's work under the Maritime Freedom of Manoeuvre programme.

Maritime multi-sensor fusion

Large maritime platforms like the Type 23 frigate (T23), its successor the Type 26 (T26), and the Type 45 destroyer (T45), are equipped with a multitude of sensors. By representing the ship as a networked system of heterogeneous sensors, UDRC researchers cast the problem as a DDD task. This will have extension to future 'fleet' sensing tasks (i.e. those involving multiple ships and other platforms) as well as off-board sensors such as those borne on unmanned air systems (UAS). Exploitation has been through Dstl's Maritime programmes as well as the MarCE industry partnership. Dstl has provided ship-borne multi-sensor data for which time-dependent uncertainties in sensor position and orientation can be significant. This is a problem of current interest; Dstl has identified the geo-spatial and temporal referencing (G&TR) aspects as those that benefit most from this technology and the developed algorithms are aimed at insertion points in GT&R systems for the T26 and T45.

SAPIENT

Sensing for Asset Protection using Integrated Electronic Networked Technology (SAPIENT) is a concept for networked autonomous sensor modules that communicate low bandwidth detection and classification messages rather than raw data. SAPIENT is being developed by Dstl under CSA funding towards a number of user scenarios including base protection, anti-vehicle area denial and counter-UAS. In all these scenarios accurate knowledge of the location and orientation of the sensors is critical to the ability to fuse the messages. Low-cost, autonomous self-localisation is a critical enabler that would avoid lengthy manual surveying of the sensors and allow such systems to be deployed at high tempo.

UDRC researchers, in collaboration with Cubica Technologies, won DASA funding to demonstrate their algorithms for sensor localisation and orientation in a network of radar and lidar sensors. The efficacy of these algorithms has been tested in networks of commercial off-the-shelf (COTS) sensors used in perimeter protection applications. Low-cost, autonomous self-localisation capability is crucial in efficient deployment of these networks.

Additional applications

Reliable detection and localisation of small aircraft such as drones is a topic of increasing defence interest. The approaches developed here are capable of providing low false alarm rate detection and accurate localisation of these vehicles. Analogous issues arise in the maritime domain in the detection of small maritime craft. In both instances there is uncertainty characterised by a non-stationary background, high false alarm rates and large numbers of other vessels. Novel and efficient *track-before-detect* (TBD) approaches[2] developed by the UDRC are capable of addressing these challenges.

3.3.2 Distributed detection, registration & fusion

The UDRC research into distributed multi-sensor processing had two main research thrusts. The first considered sensor platforms which exchange high-level information (e.g. target location) over a network. The prerequisite to fusion of such local information is its calibration to a global frame of reference. This task is conventionally carried out either manually or by using dedicated calibration sensors, such as GPS receivers. The UDRC team developed scalable algorithms for sensor calibration which do not require such dedicated sensors. These registration methods use target information and enable sensor localisation in GPS-denied or other restricted environments. The second thrust focused on signal processing with geographically dispersed transmitter and receiver networks. The UDRC team developed theoretical tools and algorithms which achieve substantial improvements in detection performance and resource management for such networks.

[2] Track-before-detect algorithms seek to dispense with the detection process. Instead they operate directly on the sensor output, be that an image, intensity map, radar I/Q or any low-level datum. The benefit is that targets at low SNR which may have escaped beneath a detection threshold can be found through what is, in effect, a longer integration. The downside is that TBD methods need to process larger data sets and tend therefore to be much more computationally expensive.

Distributed fusion and registration

In multi-sensor fusion operations, it is commonly assumed that the sensors are registered onto a common reference frame. In practice, however, registration can be non-existent or poorly calibrated and prone to drift, thus leading to decreases in target track and identity accuracy. Existing solutions to the problem have a number of shortcomings. They do not employ realistic models that capture all uncertainties in the problem. They also fail to scale well with the number of sensors (see, for example, [21], [22]).

UDRC researchers have shown that it is possible to jointly identify and track a varying number of targets in scenarios using real data with high false-alarm rates in real time, performing registration onto a common reference frame. Each platform maintains its own estimates of the targets in the scene, and fuses information from neighbouring sensors when communication permits, trading off accuracy against latency. These results are theoretically well-grounded and scalable for network self-calibration problems. The method exploits the measurements of the targets collected from the surveillance region. These quantify target parameters with varying degrees of uncertainty. The algorithm then uses them to locate nodes with respect to the origin of a network coordinate system.

In general, the computational cost of jointly processing data from all nodes grows exponentially [23]; at every scan, measurements are due to targets and false alarms. The number and assignment of these is unknown. It is therefore advantageous to filter uncertainties locally at the sensor platform. This ensures communication only of essential information and prevents unnecessary use of network resources [21]. The UDRC calibration and localisation algorithm uses local filter outputs and thereby provides a substantial improvement in scalability with the network size. This is possible, however, only if one can trade-off the exact solution of the problem with well-engineered approximations. For localisation, finding such approximations is non-trivial, and has been the focus of this work.

Self-localisation using pseudo-likelihoods

In order to address issues of scalability, the UDRC team developed a modelling framework that approximates the intractable exact model of the multi-sensor calibration problem by combining local models. As a result a configuration of sensor calibration parameters (e.g. sensor locations) is evaluated based solely on individual single sensor data streams. No joint processing is required. This key feature uses message passing. Sensor localisation is found by exploring possible sensor configurations to find the most likely one. This search is performed efficiently by creating samples in those regions of the space containing likely values.

The first family of the approximate models are built upon novel structures referred to as dual-term separable likelihoods. UDRC researchers first introduced these in [24]. In [25], it was proved that this approximation is accurate provided that the sensors are able to locate the objects in their field-of-view. Extensions of this work are capable of giving useful output when the sensor fields of view overlap only partially [26]. A second family of approximate models [27] has been shown to be an accurate approximation for parameter estimation in multi-sensor state space models [28]. In order to exploit this method when there are multiple objects, extra attention needs to be paid to data association uncertainties. Key to scalable inference using this model is an empirical Bayesian interpretation of hypothesis-based local filtering [28].

The self-localisation algorithms use Monte Carlo methods within a variational inference technique known as belief propagation (BP). Monte Carlo BP iteratively generates new location samples until these samples accumulate around the most likely configuration. Efficiency in sampling is achieved by exploiting the fact that one of the sensor platforms is at the origin of the coordinate system. Starting from this sensor, pairwise likeli-

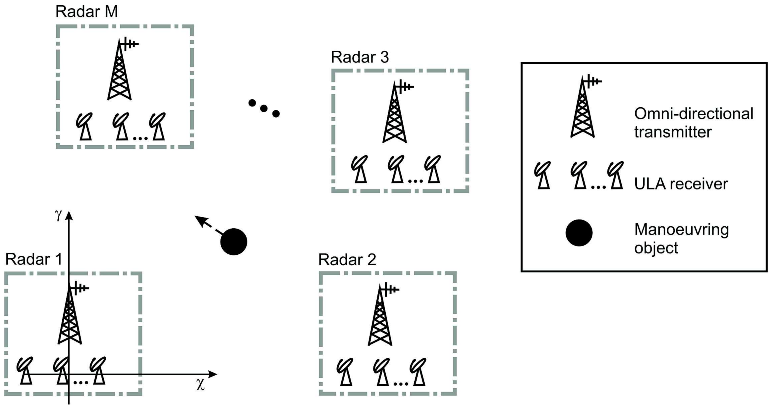

Figure 3.10: A MIMO view of distributed staring array radars emitting orthogonal probing waveforms. ULA stands for Uniform Linear Array.

hoods are used to find adequate prior distributions based on data. This technique, referred to as empirical Bayes, improves the sample efficiency and convergence properties of BP.

Detection with geographically distributed sensors

The second research thrust aims to address the challenge of detecting manoeuvring low SNR objects using modified TBD methods. Geographically distributed transmitter elements provide the benefit of sensing diversity by illuminating an object from different aspect angles [29]. UDRC research has considered MIMO configurations composed of components with a co-located omni-directional transmitter and a staring array receiver. Each pair can be treated as a standalone radar and they coexist by transmitting orthogonal probing waveforms [30] (see figure 3.10).

Detection is a statistical hypothesis testing problem, the solution to which assesses the content of received signals containing reflected versions of the transmitted waveform. Such tests span a time window, the length of which should be long enough to collect sufficient signal to rule out the noise only hypothesis. For dim objects a longer time window is needed. Target manoeuvres complicate this search. In order to locate the correct signal samples for the detection test, the trajectory of the object needs to be estimated.

Geographical diversity leads to many reflections at any receiver whose data can be integrated for detection. In order to make use of these reflections, however, accurate temporal calibration of the transmitter is required. This level of synchronisation is extremely difficult to achieve with geographically distributed transmitter elements. Existing methods often make unrealistic assumptions and cannot guarantee an acceptable degree of detection performance in the case of manoeuvring low SNR targets. There are also few accurate algorithmic methods for finding the synchronisation of non co-located transmitter-receiver pairs.

The UDRC approach evaluates statistical detection tests on measurements over arbitrary time windows [31]. One challenge addressed by the UDRC algorithm is that the reflection strength corresponding to the hypothesised target also needs to be estimated. The UDRC team showed that this quantity can be found using the measurements from staring array receivers. This is key as the number of measurements collected is often not sufficient for an accurate estimate of the target strength [32] which results in failure to detect reliably. A new method for synchronisation in spatially-separated MIMO systems using the object trajectory as a reference has been presented in [33].

3.3.3 Adaptive waveform design in MIMO active sensing

UDRC research addressed the problem of how to construct a radar waveform for a MIMO array to best estimate target parameters. Typically, in MIMO radar (and sonar) systems the received signal is a non-linear function of the target parameters. The researchers extended existing work on this subject to incorporate this non-linearity into general active sensing MIMO arrays. A MIMO active sensing system adaptively designs the transmit waveforms such that the location angles of a known number of targets are estimated with minimum expected variance. This is referred to as minimum mean squared error (MMSE) design in signal processing literature.

An accepted mathematical formulation for this problem exists, though it only provides approximations for the optimal waveform design. The primary purpose of the UDRC research for this application was to derive exact MMSE waveforms for active sensing systems, and to apply these in simulations based on real-world systems and scenarios of interest. The theoretical expression for MMSE adaptive waveform design was derived in [34]. This expression leads to challenging implementation questions, as its evaluation is computationally expensive. The UDRC solution reduced computational load using a novel sampling strategy [34].

Numerical simulations of one and two target scenarios showed that the MMSE adaptive waveform method outperforms both the non-adaptive method, and an existing approximate method for MMSE waveform design when targets are static [34]. Further preliminary results indicate that this improvement holds in the case where targets are moving, and that the gain may be even greater.

Having achieved its primary objective, this work progressed to ask the question of whether MMSE is the best optimisation metric for adaptive waveform design in MIMO systems. One outcome of this analysis was that, in the case where the parameters associated with one target are relatively uncertain, minimising the largest eigenvalue of the error covariance matrix for the target parameters is a better optimisation method than a MMSE criterion [35]. The researchers speculated that in order to optimise waveform design, real-world MIMO systems may require a higher degree of waveform control than current technology permits.

3.3.4 Extending and exploiting multi-sensor processing systems

Automatic calibration has been demonstrated on real data collected using a SAPIENT-compliant network of radar and lidar sensors. The theory and algorithms developed by the UDRC exploit Monte Carlo methods within BP to generate candidate sensor configurations and evaluate their efficacy. The differences in likelihood, however, are typically negligible for almost all configurations. The UDRC researchers have used this fact to develop novel sampling strategies to improve efficiency. This approach has the potential to allow rapid deployment and robust operation of sensor networks in many different scenarios. Further research of this type will extend the range of applications.

The modelling approach for detection problems anticipates a number of interesting research directions. For example, the extraction of signal features (e.g. Doppler) for target classification. The UDRC algorithm can track target reflections for comparatively long time periods which aids robust feature extraction. Integration of this capability with detection allows automatic discrimination of objects of interest (e.g. drones from birds).

A further research direction relates to the fusion of data from different sensing modalities and resolutions. The existing literature on multi-modal sensor fusion largely considers the combination of information at a decision level. The UDRC model allows for fusion from different sensors at the data or information level. Contributions in this area could have a significant impact in sensing applications including those for multi-sensor autonomous systems.

The work undertaken on radar waveform design has motivated two further research directions. Firstly, developing better methods for optimisation in adaptive waveform design. In particular, finding features of the derived adaptive waveform that enable a step improvement in the optimisation and reduce the computational load. Secondly, the UDRC research has shown that the effectiveness of adaptive waveform design is dependent on the validity of the target model. It is therefore necessary to investigate whether existing statistical characterisations of the target are sufficient for adaptive waveform design.

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Chapter 4

Object detection, localisation and sensor management

Acquiring timely situation awareness in the networked battlespace hinges on appropriate tasking of sensors, summarised in figure 4.1. In order to do this effectively, the states of sensors, targets, the environment and other context must be well estimated. The precision of these estimates is often not as important as a quantification of the uncertainty in our knowledge.

In many cases where there is freedom to alter the states of sensors, interventions that lower the uncertainty and improve situation awareness can be made. This is called sensor management and can be thought of as an optimisation over many dimensions (e.g. sensor field of view, sensor location, processing location, bandwidth, processor resources) which can vary between missions. As the state-space scales up to many sensors and many targets this optimisation quickly becomes intractable. Sensor management is also a strong function of our knowledge of target dynamics and the constraints imposed by the environment, mission, and doctrine, amongst other things. In defence, these decisions are generally made by a human. If

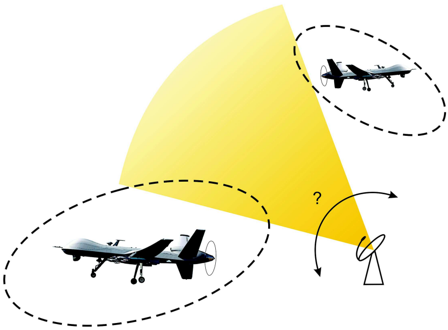

Figure 4.1: A graphic showing target locations together with an estimate of the uncertainty in their location (dashed ellipses). The sensor has a range of options each of which will affect the uncertainty in different ways. Effective sensor management hinges on quantified prediction of the potential effect of each putative measurement.

situation awareness is to be realised autonomously, then research must address the interface between sensing, tracking, control and decision making.

4.1 Incorporating domain knowledge using Bayesian inference

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Domain knowledge and contextual information is used by all humans when making inference decisions (e.g. tracking, classification). This is currently less true of machines which have tended to apply fixed rules or algorithms in a particular situation with limited opportunity to transfer these methods into new areas. When combining or fusing data and information, *Bayes rule* is a powerful statistical tool that tells one how to combine measurements produced by some presumed process (called the *likelihood*) with prior information and evidence (the actual measurements) in a rigorous and optimal way.

$$\text{Posterior probability} = \frac{\text{Prior} \times \text{Likelihood}}{\text{Evidence}} \tag{4.1}$$

Bayes rule is of practical value to humans and autonomous systems alike, but there is currently no general approach for the incorporation of domain knowledge into practical Bayesian inference machines. The UDRC aimed to establish a framework by which all information and data available to agents in a networked environment can be incorporated into situation awareness and decision making. New signal processing algorithms adaptive to operational environments have been developed by exploiting domain knowledge. Extensions have been made to sensor platforms operating in a networked environment by fusing different types of information. This work has produced research outputs which have been applied to a number of different domains.

Firstly, the UDRC used domain knowledge to reduce uncertainties in object tracking. This is achieved by making use of knowledge that may be difficult to capture, represent or exploit in both the modelling and signal processing stages of existing approaches. In the context of moving object tracking, constraints are due to road networks, terrain and other geographical information, as well as particular sensor properties and characteristics (e.g. blind zones in GMTI radar).

Secondly, an object may have different and predictable stages or modes of its movement (e.g. stop, acceleration, constant motion for a ground vehicle, or the boost, coast and re-entry stage of a ballistic missile). So-called *Markov Jump* models can represent the behaviour of a wide range of moving objects and their distinct operational modes. Switches from one mode to another are affected by many domain-specific factors, including interactions with the environment or other objects, or the nature of the moving object. The current Markov Jump models are not able to capture these aspects of domain knowledge – something a human does almost instinctively. UDRC researchers have developed a new modelling approach, referred to as *State Dependent Transition* (or Hybrid Markov Jump) to model the dependency of the modes, their transitions, and physical constraints on the operational environment. Based on these new modelling approaches, a Bayesian tracking framework was proposed to develop context-aware tracking algorithms. Efficient implementations have been developed. Several case studies have been investigated to demonstrate the efficiency of the proposed modelling and tracking algorithms, including UAV-mounted GMTI radar tracking ground moving vehicles [1], [2], ballistic missile tracking and stage estimation [3], [4], and multiple target tracking [5]. Detailed numerical and simulation studies have shown improved performance in comparison with existing approaches.

The rest of this section consists of a more in-depth examination of a single application where domain knowledge is used to increase inference accuracy using a Bayesian framework. The example is drawn from sensing for the location and classification of Chemical, Biological and Radiological (CBR) releases.

4.1.1 CBR source term estimation using autonomous vehicles

Hazardous substances released into the atmosphere pose both an immediate and delayed risk to human health. A prompt and accurate prediction of where the material will disperse and deposit is therefore required to enable first and specialist responders to undertake appropriate mitigation strategies. Hazard predictions, however, require accurate knowledge of the release parameters (the so-called *source term*), as well as the local meteorological information. In many situations this information may be unknown, or highly variable. CBR sensor readings will indicate the presence of a hazardous material and this must be turned rapidly into a warning in order to ensure the safety of personnel in the vicinity and maintain operational tempo. This currently requires either a static network of pre-deployed CBR sensors, which can be costly and necessitate substantial planning, or the manual collection of sensor measurements, which places responders at risk. The utility of unmanned autonomous vehicles with integrated CBR sensors is that they provide a reconnaissance and survey capability for obtaining real-time, targeted – i.e. most informative – measurements without endangering personnel.

The work undertaken during UDRC phase 2 has developed an algorithm to autonomously guide an unmanned vehicle to the most informative measurement locations in order to simultaneously search for and estimate the parameters of a hazardous release. Domain knowledge is incorporated by way of meteorological information and an atmospheric dispersion model to forecast the spread of the hazardous material. The known or estimated physical properties of the source can also be used.

The UDRC method can be used independently, or as a supplement to a static network of sensors that may be deployed around a specific area of interest, such as the perimeter of a military base. The UDRC phase 2 work concluded with an experimental result, the first of its kind in the literature, where a robot equipped with a gas sensor was guided by the algorithm to estimate the source term of a release.

The need for autonomous CBR source term estimation

A system capable of automated collection of informative CBR sensor data will enhance situation awareness through more accurate reconstruction of the source term. This results in better hazard predictions that enhance decision-making under CBR threats, maintain operational tempo, and ultimately save lives. Such a system could be used independently or in concert with an existing Dstl source-term estimation (STE) capability (designed for continuous monitoring of static CBR sensors and collectors), to provide protection of military or civilian personnel and assets or areas of interest. Deployment of such a system on a lightweight, low-burden, mobile platform, e.g. a UAV, enables forward deployment of an STE capability, providing real-time CBR situation awareness at the tactical level. This allows the tactical commander to adopt alternative courses of action, enhancing survivability and avoiding contamination of critical assets.

It is envisaged that the technology be used by trained specialists for the following:

- reconnaissance and survey of an area to identify and characterise a suspected CBR release, or to eliminate the possibility of a potential hazard;
- routine monitoring of the air in and around a specific area of interest (e.g. military base, city, major event);
- reactive deployment of autonomous vehicles to collect additional data in response to a static sensor alarm;
- data gathering to quantify and monitor contamination levels of a known CBR release, e.g. a forensic investigation following a strike on a chemical facility or a toxic industrial accident.

The capability could be further enhanced to include non-CBR data. The use of Intelligence, Surveillance and Reconnaissance (ISR) assets, for example, would enable target acquisition capabilities to further refine estimated release locations via identification of a suspect vehicle at or near the inferred release location. Integration of all-source information will reduce the uncertainty in the estimated source terms and improve the hazard prediction accuracy.

CBR source-term estimation research

An autonomous search and estimation algorithm was developed by UDRC researchers to guide a robot to localise and characterise a source of hazardous material. Estimation of the source term is strongly influenced by domain knowledge and is a function of the release location (e.g. latitude and longitude), the release mass rate (in $\mathrm{kg\,s^{-1}}$), the diffusivity and average lifetime of the dispersing material, as well as the wind speed, wind direction and other meteorological parameters. See [6] for a more complete description. To expedite the inference, meteorological measurements are used to provide a starting point (i.e. a prior) for wind speed and direction.

Using the UDRC algorithm, the robot, beginning from an arbitrary location and equipped with a simple concentration sensor, navigates its way through the environment collecting measurements of the hazard at set time intervals. At each time step the robot will choose from an admissible set of actions and move to the location that is expected to yield the most informative data [7].

A probabilistic framework was used to estimate the source parameters accommodating the large uncertainties in the hazard concentration readings from the sensor [7]. The state of knowledge regarding the source parameters was represented by a posterior probability distribution which was continuously updated in response to new sensor data, using Bayes' rule (equation 4.1).

The initial prior distributions of the source parameters were assumed to be given; either provided through sensory data or by user input. If information concerning the source term was available prior to the search, it could be used by way of an appropriate distribution to represent the prior knowledge of the release. However, in the absence of information, as will normally be the case, the prior can be set to an uninformative distribution. In subsequent iterations, the prior distributions were replaced to reflect the information gained from the previous sequence. The Bayesian estimation of the source term parameters was implemented in a recursive fashion, using a sequential Monte Carlo algorithm [7].

The next step was to choose the manoeuvre that is expected to be the most informative from an admissible set of actions. The reward or utility function for sensor planning was inspired by the literature on optimal experiment design. The purpose of the reward function is to represent the information gained on the estimated source term parameters given the next sensor reading. Different functions can be adopted. However, since the future measurement is generally unknown, it was suggested that the optimal sensor placement should be the one that maximises the expected utility of the subsequent measurement. The experimental design problem was adapted to direct a mobile sensor, where the choice of the next experiment is the movement of the sensor. The value of the expected utility was approximated by importance sampling techniques, e.g. [8].

The sensor control strategy undertook the full search using a single framework which balanced exploration and exploitation, incorporating the estimates of the source parameters. The emergent behaviour was characterised by explorative behaviour when the posterior distributions were less informative, and exploitative behaviour, i.e. moving towards the source, as the posterior distributions became more informative. In the case of a continuous, ongoing release this approach naturally guides the robot towards the source location, as the posterior estimate becomes more certain. An example can be seen in figure 4.2. Here the route taken by the mobile sensor is shown along with the posterior distribution for release location at four discrete points in time.

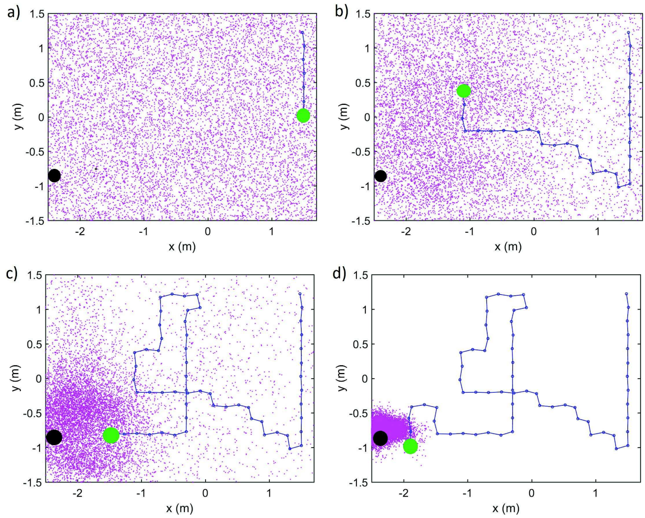

Figure 4.2: An illustrative STE search using an autonomous robot. Panels show time steps: (a) 7, (b) 32, (c) 58, and (d) 65. The green dot represents the current position of the robot having followed the blue line and made observations at positions indicated by the blue dots. The true location of the source is shown by the black dot and the small pink dots represent the random samples from the estimation algorithm.

Technology demonstration via the Defence and Security Accelerator

The fundamental research conducted by UDRC researchers was used as the basis for a proposal which won DASA funding under a themed call for Autonomy in Hazardous Scene Assessment (AHSA). The project was called *Autonomous Bayesian search for hazardous sources*. Whilst also contributing to the development of the STE algorithm, the emphasis of the AHSA project was on verifying the approach in a live demonstration under experimental conditions.

In the live demonstration, smoke released from burning incense sticks was used to simulate a hazardous release in an indoor area. A TurtleBot robot was used as an unmanned

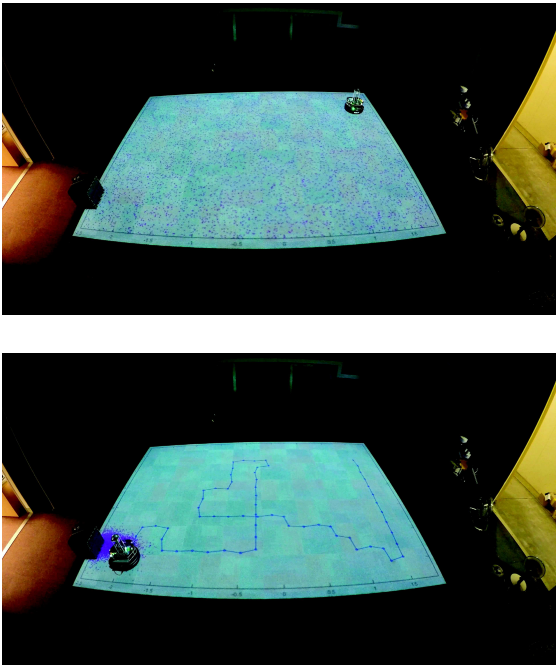

Figure 4.3: Photographs from the start (top) and end (bottom) of an illustrative run with two sources.

ground vehicle, and was equipped with a low-cost metal oxide sensor to measure smoke concentration. Smoke measurements, position coordinates and velocity commands were shared between the robot and a ground control station using the Robot Operating System, a standard tool used in research robotics.

Figure 4.3 shows photographs taken at the start and end of the demonstration. In this example, the incense sticks are positioned on the left-hand side of the room. The starting position of the TurtleBot (top right corner of the picture) can be seen in the top image of figure 4.3, while the final position can be seen in the bottom image, along with the path the robot took.

The posterior density estimates of the source parameters for

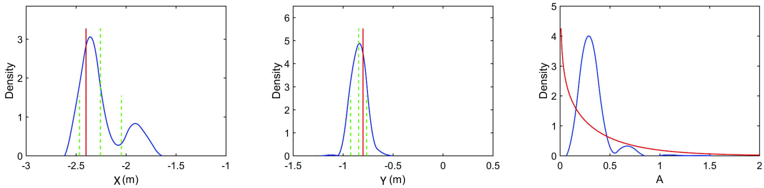

Figure 4.4: Posterior density estimates of the location (x and y coordinates) and the scaled release rate, A, after an illustrative run with two sticks. The blue curve indicates the posterior estimate with the dashed green lines representing the mean and standard deviation of the estimate. The vertical red line (for x and y) indicates the truth, and the red curve (for A) represents the prior distribution.

the demonstration run are shown in figures 4.4 and 4.5. The experiments were run several times to ensure that the system was reliable under the experimental conditions shown and release location estimates were consistently found to be within 10cm of the true source location.

In addition to demonstrating the autonomous STE capability, the AHSA project also explored implementation issues on a UAS. The study, with project partner Swarm Systems Ltd, addressed mechanical integration, electronics integration, communications, control and specialist module design. The system used in the study was the Owl 4 Nano AV, which is a small quadrotor system weighing less than 200g. The study assessed the feasibility and system design issues of adding a chemical concentration sensor to the existing on-board sensor suite of electro-optical (EO) visible-band and IR cameras mounted on a single axis gimbal. The study also reviewed low-cost concentration sensors suitable for integration onto the platform.

The successful live demonstration and promising UAS integration study lead to satisfactory completion of the first phase of the AHSA project. On the strength of the phase 1 demonstration and outputs, funding was secured for phase 2 of AHSA, where the system will be demonstrated running on a UAV in

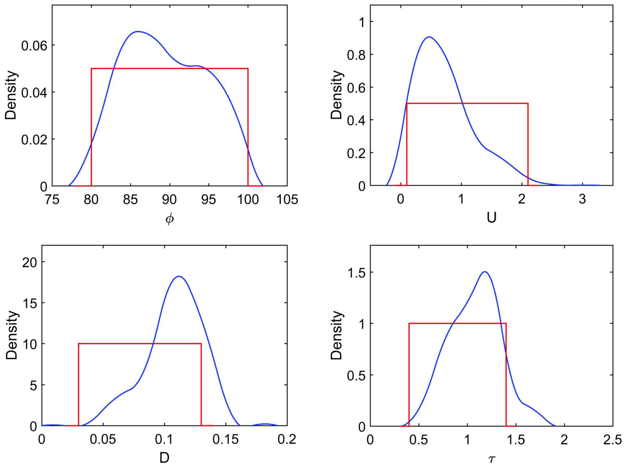

Figure 4.5: The source parameter estimates at the end of the experiment: (a) wind direction ϕ_0, (b) wind speed U_0, (c) diffusivity D_0 and (d) lifetime τ_0. The red line indicates the prior and the blue curve is the estimate.

an outdoor environment.

4.1.2 Outputs of theoretical and applied STE research

A state-of-the-art information-theoretic technique to estimate the source term of a hazardous atmospheric release has been developed and tested in experimental conditions. Previously in the literature, testing of these algorithms had been limited to simulations, historical datasets, or experiments using a thermal source. This work marks the first implementation of an autonomous source estimation algorithm in which a mobile sensor platform was guided in real-time using information theoretic principles. The results of the experiments demonstrate successful use of the system, and how the location of a dispersing source can be estimated using a low cost gas sensor in relatively short time. The following actions and recommendations will improve the performance of the system, extend its capabilities and work toward an operational STE capability.

- Phase 2 of AHSA will develop the system to operate in three-dimensional space in order to run on-board an airborne platform instead of a ground vehicle. Outdoor field trials using a UAV will be undertaken.
- Phase 2 AHSA will also explore the feasibility of mounting a chemical agent sensor on-board a UAV. This should include assessment of the impact of UAV rotor blades on observed concentration levels.
- The algorithm should be adapted to infer instantaneous and finite duration continuous releases that have occurred in the immediate past, in addition to the current infinite duration (i.e. continuing) releases.
- The ability to operate efficiently in cluttered or urban environments should be increased. This will involve several steps to improve the source estimation and UAV path-planning algorithm.
- Methods to integrate the system with existing STE capabilities designed to support static sensor networks should be explored.
- The ability to identify and map the boundary of a contamination zone, rather than the source of the hazard would be a valuable and straightforward addition to the algorithm.

4.2 Multi-object estimation and sensor management

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When sensors can be adjusted in real time, considerable choice regarding the collection of future measurements exists. Some metric is therefore necessary that evaluates the outcome of different sensing choices and its assessment is central to autonomous sensor management. A commonly used quantity for this purpose measures the potential reduction in uncertainty in the estimated target state, thereby providing information on the value of each putative measurement. State-of-the-art approaches to sensor management conventionally fall into two distinct types, based on either information-theoretic or task-based metrics. The first type assumes the objective of maintaining information that is as extensive and as complete as possible. The second type focuses on parameters that are specifically extracted to be well matched to the user's task. UDRC phase 2 research has developed solutions pertinent to metrics of each type.

Of course, where to point the sensors requires an appropriate estimate of sensor states as well as multiple target states. The development of multiple-target detection and tracking algorithms (also sometimes referred to as filters) initially arose from the extension of single-target algorithms to the multi-object case. In multi-object state estimation, the unknown data association between the targets and the measurements is hypothesised, and single-target filters are run in parallel for every association hypothesis [9]. This data association scheme involves combinatorial mathematics, and scales very poorly with the size of the tracking problem: in the general case, the complexity of these solutions increases rapidly with the number of targets and collected measurements. As an example, in the case of 5 targets and 5 ambiguous detections the number of possible target-detection associations at a single point in time can be over 30 million.

An alternative approach, proposed in the early 2000s, called Finite Set Statistics (FISST) [10], [11], represents the whole population of targets as a single set of objects, rather than a collection of individual tracks. The FISST framework allows for the rigorous modelling of multi-object detection and tracking problems, accounting for all sources of uncertainty (e.g. target dynamics, sensor measurement noise, probability of detection, false alarm rate). The FISST framework has proven far less computationally demanding than approaches that require explicit data association and is able to handle complex multi-target, multi-sensor tracking scenarios with thousands of targets in real time. While well adapted to large scale scenarios, the first generation of multi-target tracking techniques derived from FISST lacked a measure of uncertainty in the local estimate (i.e. in any desired region of the surveillance scene) of the number of targets. This makes them unsuitable for use in principled sensor management algorithms.

The work undertaken in UDRC phase 2 took FISST as a framework and sought to incorporate second-order statistical information, i.e. uncertainty estimates. In order to achieve this, the fundamentals of the theory were revisited through the more general point process theory; novel statistical tools were introduced for the description of multi-target states, and new filtering solutions developed to exploit those tools.

4.2.1 Autonomous sensor management for defence

Efficient sensor management algorithms are useful in a range of congested and contested military domains, especially where sensor use is constrained. They are also applicable to sensors with a field of view that is small with respect to the surveillance area so complete coverage is not possible without reorientation. Examples of this type of problem occur in radar and EO sensing. Networks of sensors where reconfiguration, relocation or activation of sensing nodes are considerations for an operator (e.g. electronic surveillance) are also situations which will benefit from this research.

The sensor management algorithms developed under the UDRC phase 2 are relevant to analyses of populations where estimating target identity over the whole course of scenario may not be of primary interest, but where the number of objects is significant. This is a good description of swarms of drones – of interest in counter UAS scenarios, or for space situation awareness (SSA), where the density of orbiting debris rather than its individual composition, may be of primary concern. The research described in this section is also well suited to simultaneous tracking and sensor registration in the above-water maritime domain.

Autonomy is an important exploitation route for sensor management algorithms. Indeed, future autonomous systems cannot function without the capacity to decide when and where to make sensor measurements. Furthermore, without adequate consideration of the efficiency and effectiveness of these observations a system may compromise its situation awareness, posing a risk to its mission or itself. These considerations are compounded where autonomous systems work in groups sharing information.

4.2.2 Theoretical advances in estimation and sensor management

Higher-order statistics for multi-target tracking

Recent progress in multi-object filtering has led to algorithms that compute the so-called *first-order moment* of multi-object distributions [12]. This allows the number of targets in an arbitrarily selected region to be estimated. In the UDRC phase 2, researchers developed explicit methods for the computation of *second-order* statistics for multi-object filters [13]. This quantifies the level of uncertainty in target state and number in arbitrary regions and so makes information-theoretic sensor management methods possible.

Describing the output of the filters with higher-order moments allows for a more subtle analysis of the acquired information. Extracting second-order information is particularly important in applications where the confidence in the acquired information about the observed system is at least as important as the information itself. Sensor management problems can therefore be solved autonomously, with information-based decisions focusing attention on regions where the expected gain in the acquired information would be greatest.

Current first-order moment methods are unsatisfactory in situations where little is known a priori about the populations of objects to be estimated. An example is provided by a sensor whose false alarm rate is roughly constant, but where unpredictable 'bursts' of false alarms sometimes occur (automated detection algorithms on cameras on UAVs sometimes behave like this). In these instances the estimated number of targets is not well tracked. UDRC researchers addressed this problem by developing a method based on the *Panjer distribution*. This derives from the theory of multi-target point processes and offers more flexibility than commonly used distributions (e.g. Poisson) in the description of the size of a population of objects. Results, shown in figure 4.6, demonstrate that while Poissonian

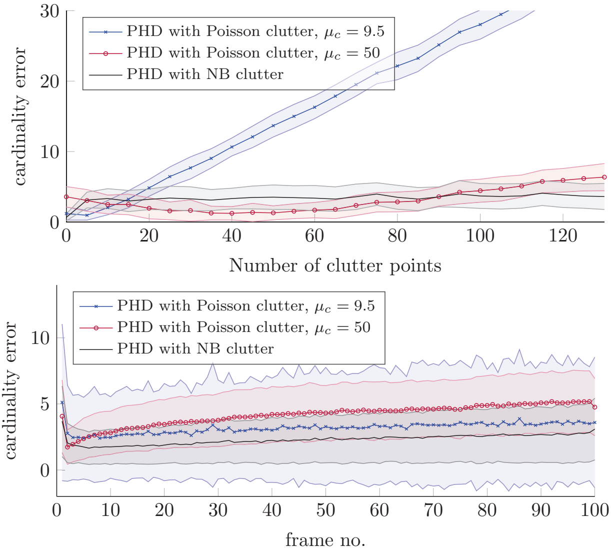

Figure 4.6: Mean error and variance bounds in the number of estimated targets (y) for two (PHD) filters with varying degrees of Poissonian clutter, and the UDRC-developed filter with negative binomial (NB) clutter. Top: the x-axis shows the number of simulated clutter points. Bottom: the x-axis represents time in a scenario where the clutter has a NB distribution with mean 9.5 and variance 190.

filters behave well when the actual clutter rate corresponds to the free parameter (μ_c), the UDRC-developed filter is able to give good cardinality estimates over a range of clutter densities. In cases where sensor false alarm rate is unpredictable, the mean and variance of the cardinality error for the UDRC filter is smaller than the other filters, indicating it gives more stable estimates [14].

Joint estimation of target states and sensor calibration

There are many multi-object tracking problems that require estimation of parameters which are common to all objects or related to the sensor profile. Examples of these include registration of multiple sensors, estimating clutter profiles, and autonomous vehicle self-localisation. Typically, these parameters are estimated separately from the states of the targets, which can lead to systematic errors or overconfidence in the estimates. The UDRC team developed methods of estimating the multi-target state jointly with parameters common to multiple targets or related to the sensor configuration, using first order moment methods as a basis. Initially studied for target tracking applications [15], this method has been applied to the joint triangulation of multiple objects and calibrating cameras [16], estimating sensor drift in microscopes [17] and telescopes [18], distributed multi-sensor localisation [19], and clutter-rate estimation [20]. It has also been developed, in collaboration with Dstl, for jointly calibrating a camera and a radar based on shipping traffic in a maritime surveillance application (see §4.2.3).

Estimation of object spawning events

Tracks which split to form other tracks create issues for many estimation algorithms. A real example of this problem is the risk posed to space-based assets through the fragmentation of orbiting objects. Early identification of such events is clearly critically important to reduce the risk from collisions. The tracking of objects created during such fragmentation poses a challenge for current multi-target trackers. By exploiting their understanding of point process theory, the UDRC researchers proposed the first principled derivation of the Cardinalised Probability Hypothesis Density filter, a first-order FISST-based filter, with arbitrary spontaneous birth and spawning processes. This has been applied to spawning target processes relevant to SSA [21].

Sensor management for uncertain populations of targets

An information-theoretic solution to the sensor management problem, building on estimation work, was proposed by the UDRC in [22]. The metric developed can be tailored so as to put emphasis either on specific regions within the surveillance area or on specific tracks from within a population. This capability is not currently available to other multi-object filters. For sensor management purposes a distinction is made between previously observed and yet to be detected objects, thus providing a principled distinction between the sensing actions aimed at exploitation ('tracking mode') and exploration ('search mode'). This has clear applications for operators concerned with maintaining track custody in situations where new targets are expected to emerge. Second-order statistics describing the object number when evaluated over arbitrary regions in the surveillance area were also proposed as metrics by which to undertake sensor management [13]. The variance inherent in these estimates provides a measure of reliability for the results, making them a particularly useful choice for sensor management.

4.2.3 Applications of sensor management algorithms

Multi-object estimation for space situation awareness

The detection and tracking of orbiting objects is required for the assessment of potential collisions, sensor scheduling, data downlink, among many other tasks. Current catalogues, however, are deterministic in nature and provide estimates of objects without an associated measure of uncertainty [23]. This is despite the fact that neither the orbital dynamics nor the sensors' observation processes are well quantified. Choosing how and when to make observations of orbiting objects is particularly challenging. This is compounded by size of the estimation problem. NASA maintains a catalogue of around 30,000 orbiting objects, thought to be just a fraction of the true number of objects in orbit. This congestion is set to increase as the barriers to space entry drop, with non-state actors now routinely launching satellites.

The combinatorics make the implementation of traditional track-based approaches particularly challenging in orbit. Previously developed FISST-based solutions avoid explicit data associations and can therefore handle multi-object estimation problems on a much larger scale. They do not, however, maintain individual information on each target (i.e. tracks). Many applications in the context of SSA, however, require the classification of individual objects and the propagation of individual information as accurately as possible – for the assessment of collision events, for example. It also may be important to know whether particular objects are man-made, can be remotely controlled, and who has responsibility for their control.

UDRC researchers adapted their multi-object estimation and sensor management architecture to SSA. They sought to retain the advantages of track-based approaches (propagation of individual information on identified objects) whilst exploiting the advantages of their population-based methods (principled solutions, scalability). Two filtering solutions were developed. The filter for Distinguishable and Independent Stochastic Populations (DISP) [24] maintains hypotheses for possible data associations and propagates individual tracks. It also provides a rigorous probabilistic description of the population of targets and gives well-defined probabilities of existence to every track. The DISP filter also allows for the representation of groups of objects indistinguishable from one another; for example, a cloud or orbital debris following a collision can be represented as indistinguishable objects. Individual tracks will be initiated from this population when information on specific individuals is available (typically, once the cloud of debris is observed by a sensor). The DISP has been successfully illustrated on a small-scale SSA scenario [25]. It is not, however, scalable to large-scale SSA scenarios such as the maintenance of a comprehensive catalogue of objects in near-Earth orbit.

To address the larger-scale problem the researchers developed a principled approximation of the DISP filter, the filter for Hypothesised and Independent Stochastic Populations (HISP) [26]. The HISP filter relies on the same modelling assumptions as the DISP filter, and further assumes that the data association between the targets and the observations is moderately ambiguous. This is well-suited to SSA, where the distance between the orbiting objects is usually much larger than the resolution of the sensors. The HISP filter has linear complexity with the number of objects and observations, while maintaining individual tracks with associated probabilities of existence [27]. It is therefore much more scalable and can be applied to the full near-Earth catalogue of objects.

UDRC researchers established collaborations with the UK Space Agency (UKSA) and the network of sensors used for space surveillance in the UK. They worked with data from the Chilbolton Advanced Meteorological Radar (CAMRa) facility on the Chilbolton Observatory, proposing the first automated processing algorithm for Chilbolton radar data, detecting and tracking objects in the raw data obtained from the facility [28]. They also proposed a bespoke model for the Satellite Laser-Ranging facility at the Herstmonceux Observatory, and designed the first automated processing algorithm for this sensor [29]. EO data, supplied by Dstl, of satellites on short observation arcs were also processed. The researchers deployed their simultaneous tracking and registration algorithms to correct for sensor drift and jitter (see figure 4.7) [18]. The UDRC also provided advice to Fylingdales early-warning surveillance radar. A report was delivered on potential enhancements in capability that could be made by exploiting advances in sensor calibration, multi-target tracking and object orbit estimation with uncertainty.

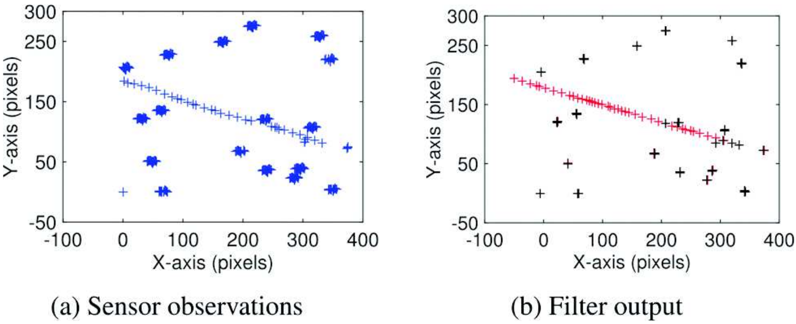

Figure 4.7: (a) Detections from images of the close passage of asteroid 2007HA through a background star field. (b) tracking results assuming Brownian sensor drift. Black crosses denote inferred stationary objects, red crosses the track of the object of interest. The tracked object entered from the right. Figure reproduced from [18].

Maritime surveillance and sensor management

Maritime navigation radars usually take a number of seconds to perform a full sweep of the region they are observing, whereas on-board optical systems typically have much faster update rates. By exploiting the high update rate and fusing EO measurements with radar, target tracks can be updated and maintained more frequently. The development of sensor fusion algorithms for maritime environments must be driven by the need to aid decision-making in the command room where operators are under pressure to respond to threats on a short timescale. Integration of information from multiple sensors can aid the operator by reducing the amount of human attention required for each sensor and improving knowledge of individual targets. It is crucial therefore that the sensor models that underpin target detection, identification, and tracking are accurate enough to ensure that fusion from multiple sources enhances rather than corrupts the global picture.

Sponsored by the Platform Systems Division at Dstl, as well as working via an enabling contract, the UDRC worked to deploy methods for multi-object tracking and sensor registration by fusing information from radar and EO sensors in maritime surveillance scenarios. The methods are based on the fully probabilistic methods for estimating multiple targets and sensor registration parameters developed under the UDRC. The key outcome was a demonstration of radar-camera registration based on measurements from boats in the Solent. The sensors were land-based. This was the first practical demonstration of autonomous calibration of heterogeneous sensors observing moving targets. It demonstrated a new capability that was previously unavailable to operators and this enhanced capability will help inform MOD's roadmap for future maritime surveillance operations.

An enabling contract addressed maritime multi-sensor calibration. Marine vessels are subject to large and non-linear variability which must be corrected in order to allow reliable tracking and handover of off-board targets. This problem is not addressed widely in the literature, and is mainly incorporated into solutions in an ad hoc manner. If, in the real world, the set of sensors is incorrectly calibrated, any fusion in the multi-sensor multi-target tracking algorithm could lead to the total loss of useful tracking information. Possible calibration or registration errors could include incorrect calibration during sensor manufacture, incorrect alignment during installation and setup, and uncontrollable factors, such as the weather in harsh environments.

UDRC researchers developed a method for jointly estimating and tracking multiple targets from a maritime radar and an infra-red search and track (IRST) system while jointly registering the sensors onto the same reference frame for fusion. The data used for registration estimation are bearings-only measurements collected by the IRST on non-cooperative targets. The main challenge in this work is that the offset angle between the radar and the IRST is unknown and must be estimated recursively along with the target states. Targets that have been observed in the surveillance region are used to estimate this offset angle. The solution builds on work undertaken in the core UDRC and the resulting framework is general, computationally inexpensive, and can be applied to a number of different sensor registration and tracking problems.

Performance analysis of multi-object tracking algorithms for image analysis

Through an enabling agreement, Dstl's Advanced Imagery Processing project sought to develop novel efficient methods for detecting and tracking low contrast targets in large, cluttered and congested images. A novel method of target detection from images was applied by UDRC researchers to discover potential measurements originating from targets. Two methods for multi-target tracking were then applied to the resulting detections to initiate target trajectories: a first-order moment method, and the second-order filter originating from core UDRC work. The accuracy of each detection method was quantified by measuring the number of detections, missed detections and false alarms at each time step. This was repeated for a range of target SNR and image sizes. The tracking accuracy was determined using standard multi-target set metrics.

The methods were compared on simulated and real data of different scenarios, varying false alarm rates. The second-order filter showed significant advantages in terms of estimation of the number of targets, in lower signal and higher noise situations. The power of the second order filter lies in the additional parameter that propagates more information than the first order filter. It typically has a lower variance in the estimated number of targets. It also responds quickly to changes in target number. The filters were demonstrated to Dstl in a range of different scenarios. It was shown that they have similar performance across scenarios, though these do not probe all possible configurations and it is anticipated that the second-order filter would perform better in scenarios with higher clutter variance.

4.2.4 Further exploitation of tracking and sensor management algorithms

A wide variety of tracking applications will benefit from the advent of second-order multi-object filters. Multi-object detection and tracking problems currently addressed using first-order methods should be assessed for suitability against second-order methods. The improved accuracy must be balanced against the potential increased computational cost. In cases where more computationally-heavy methods are used, reduced complexity methods should be tested and loss in tracking performance measured using standard tracking metrics.

The efficiency of the HISP filter could be improved. Most of the tasks performed by the HISP filter are currently undertaken independently for each track; a parallel implementation of the filter would thus improve the computational efficiency of the algorithm significantly. This would have immediate exploitation potential in SSA.

Multi-target tracking methods which exploit higher order statistics should be developed for application to sensor management scenarios. The newly developed Panjer filter should be further incorporated into the sensor management scheme. Quantitative analysis of the variance-based information-theoretic metric as a means to select from sensing options is required.

All SSA sensor models should be integrated into a multi-object architecture. This could provide a single UK SSA multi-object detection and tracking architecture. The multi-object tracking architecture should be flexible enough to allow for the selection of either the DISP filter, the HISP filter, or other tracking solutions, depending on the scale of the problem to be addressed. Data from the Fylingdales early warning radar facility should be analysed. This is part of the UK space surveillance network, and covers a large portion of the near-Earth space over the UK. It would provide a potent addition to the sensors processed so far, could perform surveillance tasks over a large field of view and cue other sensors focussing on one object at a time (e.g. the Herstmonceux or Chilbolton sensors).

4.2.5 Royal Academy of Engineering Industrial Fellowship

Daniel Clark
February 2017 – May 2017

Dr Daniel Clark was seconded to Dstl for 3 months in early 2017 under a Royal Academy of Engineering Industrial Fellowship. During his placement he worked with a number of different teams with a broad range of application interests, including space surveillance, maritime surveillance, biological data analysis and groups with interests in image processing. Daniel's time at Dstl was spent working with Dstl scientists to demonstrate technological worth, to provide expertise in areas of potential capability enhancement, and direction for future research in sensor fusion and tracking. This has helped identify new avenues of research and areas of potential collaboration between Daniel's group and Dstl.

Daniel worked as a regular Dstl team member which gave him unprecedented access to the full range of MOD's data and operating constraints. He was thus able to provide focussed and relevant advice. In turn, Daniel was able to incorporate a new understanding into his work, informing and improving his future contributions to defence science. There continues to be strong potential for collaboration on a wide range of applications and exploitation opportunities.

4.3 Game-theoretic solutions for resource allocation and tracking

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The application of game theory could provide revolutionary solutions to the military tasks of sensor and resource management. In abstract, games can be thought of as a series of strategic decisions, in which a player's action at any point is determined in the context of alternatives available to other players. They can be cooperative or adversarial. Crucially, players are often required to make decisions in the absence of communication with, or knowledge of, other player's strategies. This has obvious parallels with scenarios where own forces must maximise an outcome but are unable to communicate (e.g. cooperative identification of a target), or where the unpredictable actions of an adversary cannot be well-modelled (e.g. mitigation of RF spectrum denial techniques).

Game theory provides a formal mathematical framework for analysing conflict and cooperation between intelligent rational decision makers. An important concept in game theory is Nash equilibrium [30], [31], a balanced state in a game where no player has any incentive to deviate from their chosen strategy after considering all of their opponent's potential strategies. This means that at the Nash equilibrium, no player can benefit by unilaterally deviating from their strategy. Practically, decisions can be made which, while not optimal, will have a predictable impact.

Table 4.1: Simple cooperative sensor game payoffs. Rows give actions available to sensor 1 and columns actions for sensor 2. Each pair of numbers give the rewards for (sensor 1, sensor 2).

		Sensor 2 observes	
		Target 1	Target 2
Sensor 1 observes	Target 1	(10,10)	(1,4)
	Target 2	(4,1)	(5,5)

A pair of toy examples which demonstrate, in small part, this power and nuance are provided by the following simple games. They involve two illuminating sensors, who cannot communicate with one another, tasked with detecting two targets in a scene. One target is high value, the other less so. In the first instance it is presumed that if both sensors go after the same target then their cooperative illumination will increase the chances of detection, since bi-static or MIMO techniques can be used (see e.g. chapter 3). If only one sensor points at a target, the chances of detection for that target are reduced. This game is summarised in table 4.1 using arbitrary payoffs[1]. Target 1 is higher value than target 2. In this instance there are a pair of Nash equilibria, where both sensors point at the same target. Although observing target 2 is sub-optimal, no benefit would be derived by either sensor unilaterally altering its strategy. It's worth noting that the 'socially optimal' outcome isn't always an equilibrium state. This can be seen by way of a second example where sensors interfere with each other, reducing the benefit of observing the same target. This is enumerated in table 4.2 simply by reducing the joint reward for observing the same target[2]

It is evident from table 4.2 that the socially optimal out-

[1]This is a variant of the canonical coordination game, *stag hunt*.

[2]Based on the *prisoner's dilemma*

Table 4.2: Simple interfering sensor game payoffs. Rows give actions available to sensor 1 and columns actions for sensor 2. Each pair of numbers give the rewards for (sensor 1, sensor 2).

		Sensor 2 observes	
		Target 1	Target 2
Sensor 1 observes	Target 1	(3,3)	(1,4)
	Target 2	(4,1)	(2,2)

come is for both sensors to observe target 1. This is not an equilibrium state, however. Only where both sensors observe target 2 will no player derive benefit by switching to observe target 1. This is the only Nash equilibrium in this game. Therefore, regardless of the other player's action, a player in this game should observe target 2 even though mutual cooperation would provide a better utility for both players. This is the best outcome for each player given that they do not know what the other will do. The power of game theory is that it provides principled methods to arrive at such equilibria and so derive beneficial strategies in the absence of communication.

4.3.1 Exploiting game theory for defence

Game theoretic ideas have applications in radar, where waveforms can be chosen for a particular purpose (e.g. to maximise the detection of a target). These choices must often be made in the absence of communication with allies or in the presence of adversaries. This concept has its most potent example in radar jamming, an adversarial game where players seek to minimise their detectability or maximise their chances of detecting an adversary. Wider applicability is possible in multi-function radar, adaptive beamforming, passive bi-static or multi-static design under uncertainty, imperfect sensor measurements and radar clutter. These applications are all relevant to the DE&S Future Combat Air System (FCAS) programme where decisions on individual sensing options will need to be made autonomously and in the presence of adversaries.

Game theory can also be used for resource allocation and detection in sensor networks. Here, tactics to dynamically optimise detection performance in a network where nodes (adversarial or coalition) are unaware of each other's strategies, but react to each other's actions, must be derived.

UDRC researchers have used game theory for analysing interaction of sensors in a network and to develop distributed resource allocation techniques. As in the toy examples, the socially optimal outcome can be obtained if there is cooperation between sensors, and in these cases, a centralised resource allocation based on *convex optimisation*[3] will provide this solution. However, a centralised approach to resource allocation may not be desirable or feasible if there is no communication between sensors or if the communication links are intermittent or insecure. The UDRC work therefore focussed on autonomous decentralised resource allocation schemes and used game theory as the means to address these problems. As has been seen, the game-theoretic method may not necessarily provide the globally optimal solution. It is designed, however, to provide a robust solution. In addition to resource allocation techniques, the UDRC team also developed game-theoretic methods for sensor detection-to-track association for multi-target tracking. This problem is a combinatorial optimisation problem (c.f. §4.2). Game theory was shown, by UDRC researchers, to provide an efficient method to solve this problem and to outperform many other methods in terms of computational complexity [32], [33].

[3]Optimisation of a so-called convex function, where there is a single maximum or minimum

Game theoretic resource allocation techniques

UDRC researchers developed distributed resource allocation algorithms using methods based on so-called *potential games*[4]. These were tested on waveform allocation problems and showed improved performance measured in terms of signal to disturbance ratio compared to benchmark techniques [34], [35]. The uniqueness of an equilibrium was proved in [34] for a scenario where allied, non-communicating radars aim to select optimal waveforms by maximising signal to disturbance ratio. This demonstrated sensors interacting strategically without the need to exchange any information. To quantify the performance, a sensor network consisting of three groups of radars was simulated. The radars within the same group could coordinate their waveform allocation, but they could not communicate with radars in other groups.

The UDRC has also developed power allocation techniques for distributed sensors [36], [37]. The researchers performed extensive Nash equilibrium analysis to demonstrate existence and uniqueness of equilibrium power allocation. This rigorous mathematical analysis demonstrated that an active sensor could use signals transmitted by others in the same group as signals of opportunity [38]. Hence, without explicit coordination, certain sensors need not illuminate targets but could act purely passively, thus deriving military benefit through resource saving and maintaining covertness. Specifically, in the case when exactly n radars in a group of M achieve the desired signal-to-interference-plus-noise ratio (SINR), then at least $M-n$ radars in that cluster remain inactive. The sensors that are inactive are determined only by the target and clutter characteristics, and are independent of the actions of the other groups and the corresponding clutter. This observation leads to the conclusion that the identity of the illuminating source is not part of the game. This observation was key for the proof of

[4] This is a game in which the incentive of each player can be expressed by the same mathematical function.

Nash equilibrium [38]. UDRC researchers showed that at the Nash equilibrium one of the radars in each group opts to remain silent, i.e. zero transmission power, but uses signal from the other radar in that group as the signal of opportunity to obtain the desired SINR for target detection [39].

Multiple sensors and multiple targets

Beamforming techniques for two-dimensional phased-MIMO arrays have been developed in [40], [41]. The UDRC further extended the power allocation and beamforming methods for a sensor network with multiple targets, consisting of both surveillance and tracking sensors using non-cooperative, partially cooperative and Stackelberg game[5] methods [42]. The primary objective of each player is to minimise its transmission power while attaining an optimal beamforming strategy and satisfying a certain detection criterion for each of the targets. Initially, UDRC researchers considered a strategic non-cooperative game, where there is no communication between the various players. Here each sensor selfishly determines its optimal beam and power allocation. This was refined into a more coordinated game incorporating a pricing mechanism. Introducing a price in the utility determination for each player enforced a minimisation in the interference induced in other sensors and increased the social utility of the system. Subsequently, the UDRC team formulated a Stackelberg game by adding a surveillance sensor to the system model, which played the role of the leader, with the remaining sensors as followers. The leader applied a pricing policy for interference charged to the followers aiming at maximizing its profit while keeping the incoming interference under a certain threshold. The proof of the existence and uniqueness of the Nash equilibrium for each scenario was also presented in [42].

[5] A Stackelberg game is a type of *leader-follower* game; a game in which one player (the leader) makes a move which is observed by the other players (followers) who then react to this move.

Robust waveform design for cognitive radars

The UDRC team developed robust waveform techniques for multi-static cognitive radars in a signal-dependent clutter environment [43], [44]. In cognitive radar design second order statistics related to clutter are often assumed to be known. This is unrealistic, as exact knowledge of the clutter parameters is difficult to obtain in practical scenarios. Hence this work addressed waveform design in the presence of uncertainty in the clutter environment, and developed both worst-case and probabilistic robust waveform design techniques. As existing methods in the literature are over-conservative and generic, UDRC researchers proposed a new approach which directly incorporated uncertainty in the radar cross-section and Doppler parameters of the clutter. Using appropriate (Taylor series) approximations, a clutter-specific stochastic optimisation was made that, while maximising the SINR of a particular radar, was able to ensure the other radars in the network reliably achieve a desired SINR [45].

Game theoretic data association for multi-target tracking

UDRC researchers developed a game theoretic approach to solve the data association problem for a varying number of targets in multi-target tracking scenarios [32], [33]. This algorithm used a filtering method to generate initial track hypotheses. The game theoretic method was then used to perform target to track association. The use of a game theory allows for computationally tractable data association in very complicated scenarios.

The UDRC team developed two tracking methods based on sequential Monte Carlo methods to produce state estimates of multiple targets [47], [48]. A further innovative multi-target tracking algorithm was developed, allowing multiple extended targets to be tracked [49]. This is particularly useful for tar-

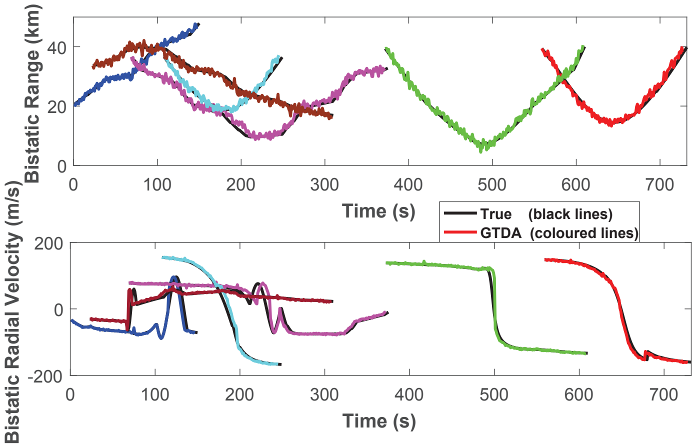

Figure 4.8: Results of game-theoretic data association. Solid black lines (visible beneath the coloured lines) represent the true flight paths on the range and radial velocity maps obtained from a live flight tracker [46]. The coloured lines denote the output of the tracker and the game-theoretic data association method.

gets with irregular shapes or extensions which produce multiple detections per scan.

To obtain target to track associations the problem of data association was formulated as a game between multiple and varying numbers of tracks (the players). To exercise the method, a passive radar experiment was devised. Aeroplanes were detected using signals of opportunity (TV transmitters) together with a low-cost antenna and an SDR to capture the signals. The UDRC technique achieved good target to track association in [33]. Figure 4.8 shows results obtained from the experiment. Notice that there are a total of six targets throughout the duration of the experiment. Three of the targets (cyan, green, red) have a U-like trajectory in range correspond to targets moving in a straight line past the closest point to the passive radar receiver. Zero (radial) velocity (bottom graph) corresponds to when targets are closest in range to the transmit-receive set-up. The other three targets have irregular trajectories indicating targets moving away after having taken off, or taking position to land at a local airport. The range and radial velocities of the true flight path (black) and the target-state-estimate after game-theoretic data association (GTDA: coloured) are shown. These results demonstrate that the proposed GTDA technique is able to properly associate the target state estimates of different targets with their corresponding tracks [32].

4.3.2 Enabling contract on temporal anomaly detection

Researchers at Loughborough participated in and won the temporal anomaly detection challenge set during the anomaly detection workshop in 2014 (see table 1.6). They were subsequently contracted to develop that submission further in collaboration with Dstl's Counter Terrorism and Security Division. Their solution used model-based spectral estimation and machine learning methods to automatically detect anomalies in temporal data. The new methods employed various statistical measures, including higher-order statistics based on support vector machines, to detect anomalies without any prior knowledge of their characteristics (i.e. in the absence of any signatures). The techniques proposed by the UDRC researchers were able to determine the start and end times of the anomalies (as required) and their frequencies with the desired accuracy. The algorithms demonstrated the ability to detect anomalies in low-to-moderate SNR environments, and when the underlying frequency of the signal drifted.

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Chapter 5

Threat refinement

This chapter describes the development of algorithms for automatic detection of anomalies from multi-dimensional, undersampled and incomplete datasets. The challenge in this work is to identify and classify behaviours as normal or abnormal, safe or threatening, from an irregular and often heterogeneous sensor network. Many defence and civilian applications can be modelled as complex networks of interconnected nodes with unknown or uncertain spatio-temporal relations. The behaviour of such heterogeneous networks can exhibit dynamic properties, reflecting evolution in both network structure (new nodes appearing and existing nodes disappearing), as well as inter-node relations.

The UDRC work has addressed not only the detection of anomalies, but also the identification of their nature and their statistical characteristics. Normal patterns and changes in behaviour have been incorporated to provide an acceptable balance between true positive rate, false positive rate, performance and computational cost. Data quality measures have been used to ensure the models of normality are not corrupted by unreliable and ambiguous data. The context for the activity of each node in complex networks offers an even more efficient anomaly detection mechanism. This has allowed the development of efficient approaches which not only detect anomalies but which also go on to classify their behaviour.

5.1 Statistical anomaly detection in communication networks

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Cyber-security affects Internet users every day, and cyber crime has become one of the largest and fastest-growing categories of crime [1]. The Internet connects billions of active devices [2] including critical infrastructure, ranging from financial services to healthcare, transportation, and energy. All of these devices are exposed to a plethora of sophisticated, potentially damaging, and frequently untraceable cyber threats.

Providing strong and reliable network security mechanisms has become critical in many areas of society, and especially so in the context of national security, as parts of the Nation's core infrastructure are constantly targeted by cyber attackers. These range from the relatively unsophisticated using methods like distributed denial of service (DDoS) attacks, to more able adversaries, so-called advanced persistent threats (APTs), who have the resources and patience to mount longer-term, more focussed, sustained campaigns. Moreover, defence users often operate their networks in hostile environments where the threat to information and the relative technical advantage is ever-changing [3]. Therefore, new and more robust detection mechanisms need to be developed to detect previously unknown threats and to ensure information integrity, availability and confidentiality.

Traditional security mechanisms, such as cryptography protocols, firewalls or antivirus, are not efficient enough to provide robust protection against APTs. Network intrusion detection systems (NIDS) have become fundamental in providing an extra level of assurance, identifying evidence of cyber attacks. NIDS are tools to identify activities which deviate from the normal behaviour of the network. Great effort has been made by researchers and private companies to increase the detection efficiency of NIDS. The use of data mining techniques and data fusion has contributed to this undertaking. Nevertheless, networks still frequently fall victim to cyber attacks.

As part of the UDRC phase 2, researchers have used statistical pattern recognition and anomaly detection methods to develop an advanced NIDS that could define the architecture of the next generation of detection systems. This NIDS includes reasoning engines supported by modules that assess the quality of the analysed dataset, manage contextual and non-contextual information about the network, handle uncertainty and deal with incongruent decisions between detection components.

5.1.1 Varieties of network intrusion detection system

A NIDS is commonly categorised as either *misuse* or *anomaly-based*. A misuse NIDS is a reactive system that uses a signature database of known indicators of attacks. This type of NIDS is generally very accurate when detecting attacks for which there exist signatures, but cannot identify new types of threat (i.e. zero-day attacks) and variants of known attacks. An anomaly-based NIDS constructs a reference from normal behaviour and flags anything that deviates significantly from this reference. Because of their statistical nature, current anomaly-based NIDS tend to raise a high number of false alerts. They are, however, potentially able to detect zero-day attacks.

Sophisticated cyber attackers try to replicate the behaviour of legitimate network users and systems in their intrusion attempts. Metrics for the detection of cyber attacks tend to be more efficient when they correlate well with the attacks. NIDS can make use of any measurement from the network and although there might be NIDS that produce accurate detection results by analysing only a single metric, this is not generally the case. The utilisation of an appropriate number of metrics and their combined use in a multi-layered approach helps improve the accuracy of the NIDS.

The need for training datasets is critically important. There are three scenarios in which this need becomes particularly evident. Firstly, using supervised NIDS requires labelled training data to learn the difference between malicious and non-malicious network traffic. Secondly, labelled datasets help to evaluate the performance of a NIDS. The labels provide the ground truth needed to compare the detection result with the correct answer. Parameters such as the detection rate provide quantifiable evidence of the effectiveness of a NIDS. Thirdly, a similar need for labelled datasets arises when feature selection (FS) techniques are used. These techniques require ground-truthed data to be able to evaluate the relevance of each metric. Unfortunately, collecting such data from real networks is often impossible. Even in controlled environments, assuring that a dataset is correctly labelled is difficult. Datasets are currently annotated through post-collection analysis, which is time-consuming and requires intensive human involvement.

Current NIDS only use measurable network traffic information from the protected system or signatures of known attacks during the intrusion detection process. These systems do not generally take information available from outside the network into account [4]. The next generation of NIDS should incorporate available high-level information (e.g. contextual information, situation awareness and expert judgment on network behaviour) within the intrusion detection process. A NIDS should be able to adapt its detection characteristics based not only on the measurable network traffic, but also on the context in which this system operates, and the information provided by the network administrator and network users.

The nature of cyber attacks has shifted from short one-off attacks toward more sophisticated longer, multi-stage attacks [5]. This type of attack requires the implementation of a number of steps in order to succeed. The main difficulty in detecting them resides in the fact that the different stages that compose a multi-stage attack may not be malicious when implemented independently. Also, the time between the stages may make the steps that compose a multi-stage attack appear uncorrelated. The stealthy manner in which these attacks are implemented makes them difficult to identify using current NIDS. Figure 5.1 represents the idea of generating an improved NIDS through the combined use of information generated by different intrusion detection components distributed throughout the network and the contextual information provided by the network administrator.

5.1.2 Defence and security need for advanced network intrusion detection

For defence exploitation, research must cover one or more of the three main information security concepts – confidentiality, integrity, and availability. The NIDS developed under UDRC phase 2 aims to improve upon all three by detecting abnormal behaviour associated with unauthorised system use. Within current cyber defence, once a threat or abnormality is detected it is passed to a network defence analyst for review. Usually, an analyst will be given more events to process than is practical; reducing false alarms is therefore critical. The application of context-aware algorithms and those that aim to reduce false alarms, such as the UDRC NIDS, is key to reducing cognitive

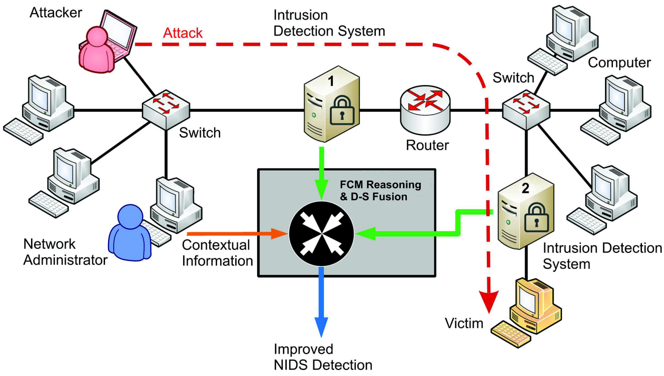

Figure 5.1: Schematic representation of the combined use of information from different NIDS and contextual information provided by the network administrator. This is an example of an attacker inside a local network.

burden on analysts.

The applicability of non-signature-based techniques within communication networks is two-fold: the detection of error for optimisation of network infrastructure, and the detection of non-normal network activity to aid cyber defence analysis. For cyber defence within MOD, methods that aid the detection of unknown threats that can mutate across fixed and wireless networks enable better confidentiality, integrity, and availability.

The UDRC-developed NIDS is capable of being deployed against insider threats as well as external attackers. It is currently developed to TRL 5 and could be exploited in many sectors; examples outside the defence and security sector include mobile device manufacturers, Internet service providers that operate open hotspots, and antivirus software companies. The NIDS has been developed in the C programming language and could therefore be integrated with embedded systems and user devices.

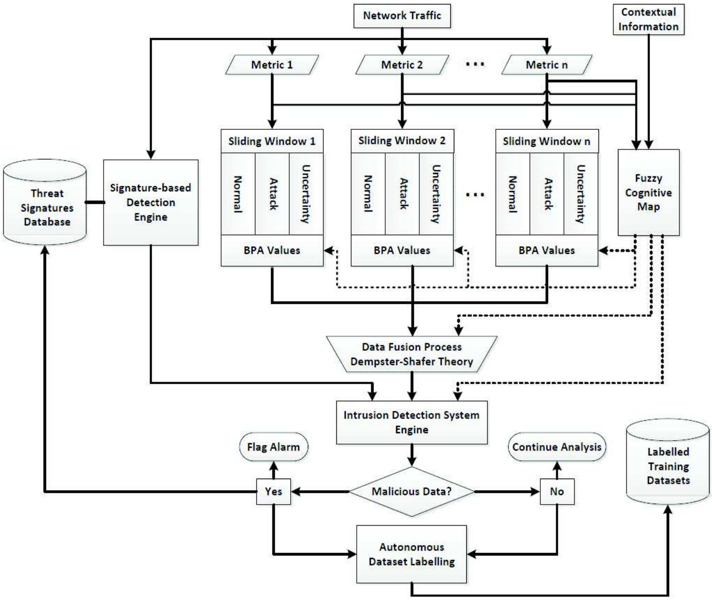

Figure 5.2: Schematic structure of the UDRC NIDS: metric extraction, signature and anomaly-based modules, data fusion process, addition of contextual information, dataset labelling process. BPA stands for belief propagation algorithm.

5.1.3 Network intrusion detection research solution

The NIDS designed by the UDRC tackles the previously described issues, with the objective of providing a stronger level of protection in communication networks. Figure 5.2 shows the schematic structure of the NIDS, including metrics from network traffic, signature and anomaly-based detection modules, the data fusion process, the addition of contextual information, and the dataset labelling process.

This NIDS built upon unsupervised anomaly-based methods developed under UDRC phase 2 [6] which are able to detect different types of attacks in real-time. The system comprises a cross-layer architecture to make a collective decision on the presence of cyber attacks. The NIDS uses the Dempster-Shafer (DS) theory of evidence [7]. DS is able to combine information from multiple and heterogeneous sources. It is suitable for detecting zero-day attacks because it does not require prior knowledge, and has the ability to manage uncertainty, which allows a large range of problems to be tackled.

The NIDS assigns a belief value for each of the possible states of the system (i.e. network traffic can be classified as malicious or non-malicious) using three unsupervised and self-adaptive statistical approaches [6]. These approaches, which autonomously adapt to the current characteristics of the network without manual intervention from an administrator, require relatively little traffic to create the reference normal behaviour used by the NIDS to identify the presence of cyber attacks.

Initially, the NIDS was solely an anomaly-based system, and did not take advantage of the use of signatures. However, in [8] UDRC researchers extended the architecture of the system to enable the combination of both misuse and anomaly-based approaches. This hybrid NIDS showed high accuracy and an ability to detect previously known and unknown attacks. In addition, the system was also able to generate new signatures using the anomaly-based approach, which can then be used by the misuse detection system.

In [9], [10] the UDRC presented a novel statistical approach to automatically generate labelled network traffic datasets using the outcome of the proposed unsupervised NIDS. Initially, the NIDS analyses an unlabelled dataset and classifies each data instance as malicious or non-malicious. This approach considers as correct only those cases that provide strong support to one of the possible system outcomes. Hence, the resulting labelled datasets are subsets of the originally unlabelled datasets. The labelled datasets can then be used to train semi-supervised techniques, such as the one-class support vector machine (SVM) [11] for FS [9], and as ground truth to evaluate other NIDS. In experiments, the dataset labelling approach was proven empirically to be highly accurate, especially when small and relatively homogeneous datasets are used. Further experiments showed that an intelligent use of uncertainty provided a significant increase in the accuracy of the labelling approach when larger and much less homogeneous datasets were analysed. In the latest experimental evaluation, this approach generated a labelled dataset comprising 588880 instances, less than 1% of which were incorrectly labelled.

In order to continue improving the efficiency of NIDS, UDRC researchers have developed different approaches by which contextual information can be added to the detection process [12]–[14]. These have made use of the pattern-of-life of network use as the main source of contextual information. A fuzzy cognitive map (FCM) [15] has been used to fine-tune the detection techniques used by the NIDS. An FCM is a tool used for prediction and decision making which can model human cognition, allowing network administrators and users to contribute their knowledge. An FCM adapts to dynamic systems that evolve over time, and handles contradictory pieces of information better than probabilistic algorithms [16]. An FCM also provides a useful mathematical framework to calculate the degree of influence that one action in a system may have upon that system. Additionally, fuzzy degrees of influence are assigned using linguistic variables, which makes FCM an excellent solution for human-machine interaction.

All of the approaches that have been developed to add contextual information by the UDRC through the use of an FCM are based on the generation or modification of the belief values used in the DS data fusion process. This high-level information can be added into the detection process at different stages, as shown in figure 5.2. The experiments that have been conducted test the effect of applying the contribution of the FCM before, during, and after the DS data fusion process. The results that have been presented in [13] confirm that the use of high-level information through an FCM improves the effectiveness of the

NIDS by reducing the number of false alarms. For example, the use of pattern-of-life provides an improvement of 10% when all metrics are combined, and a peak improvement of up to 36%, depending on the particular combination of metrics. The results confirm that adjusting the detection process prior to the data fusion makes best use of the pattern-of-life.

The UDRC-developed NIDS has proven to be highly effective in detecting different types of threats, ranging from injection attacks to virtual jamming, as well as port scanning, in different types of networks (i.e. Ethernet and Wi-Fi). Initial experimental evaluation has been conducted on WiMAX and LTE network traffic.

A number of network traffic datasets have been made publicly available [17], [18]. These datasets have been gathered from different networks, both fixed and wireless, deployed at Loughborough University. Given the scarcity of publicly available network traffic datasets, making the datasets available is an important output of the UDRC work.

Future work will examine novel methods to extract and characterise high-level information more efficiently. For example, different types of contextual information (e.g. social media) should be tested to understand whether more contextual sources improve NIDS performance, and which work best. Additionally, it is critically important to integrate and evaluate the UDRC NIDS with existing security systems in an enterprise environment in order to evaluate its efficiency against existing technologies.

5.2 Context-driven behaviour monitoring and anomaly detection

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The proliferation of sensors has resulted in rapidly increasing volumes of data being collected, filtered, manipulated and presented to analysts. To maintain an advantage in modern war-fighting this data needs to be processed quickly in order to give the appropriate military decision maker salient information in a timely fashion. There is an increasing suite of sensors which capture, or have the potential to capture, huge volumes of data. Examples with applications across defence include:

- Full motion video (FMV), often capturing multiple modalities, e.g. visible and infrared, simultaneously at high frame rates.
- Wide area motion imagery (WAMI), often at low frame rates, but covering very large areas with very high pixel counts which enables behaviour to be observed across complex scenes.

- Spectral imagery, where each pixel in the scene has some wavelength sensitivity, further sub-divided into:
  - Multi-spectral imagery, where light is collected in many more bands than the usual small number, allowing a greater discrimination between objects in the scene.
  - Hyper-spectral imagery, in which many measurements with relatively high spectral sensitivity are collected across an image, potentially enabling the identification of material in the scene by comparison with library spectra.
- Ground moving target indication (GMTI), extracting moving objects from radar sensors, often covering very large areas for significant periods of time allowing patterns and activities to be observed.

While analysts are highly capable of understanding and answering known intelligence questions they cannot be expected to extract all available information from such sensors. Anomaly detection techniques provide a means to rapidly filter and prioritise large volumes of data for further investigation. Anomaly processing techniques roughly divide into two groups; those which look for statistical outliers from a learnt model, and those which conform to modelled scenarios pre-defined as anomalous (or as a threat, and therefore of interest to the analyst). The second category is an example of pattern matching, and whilst a powerful technique, requires that the user has a detailed understanding of the behaviour they wish to identify. The former technique, on the other hand, assumes no knowledge of threat behaviours, providing a generic means to identify unexpected observations within the background or within normality. The link between what constitutes anomalous behaviour and threat behaviour is unclear, however; often it is context which allows an analyst to identify when an anomaly becomes a threat.

Despite much interest in developing automated surveillance techniques, very little work has addressed the challenges that must be overcome before wide-area surveillance based anomaly detection can be achieved. Not least is the sheer volume of data that must be processed and represented in an efficient way. Many current techniques focus on small scenes with few moving targets. Online and adaptive algorithms for learning common target motion are also scarce in the literature, and the ability to detect anomalies from partial target trajectories as they evolve is rarely considered.

The work undertaken in UDRC phase 2 focussed on the development of novel techniques to understand large volumes of data, exploiting contextual information to drive data understanding. By applying contextual understanding to observed behaviours within data, patterns can be understood and outlier points identified. This increases the ability to exploit salient information in light of contextual understanding.

5.2.1 Exploitation potential of context-driven anomaly detection

Anomaly detection provides a means to filter and prioritise data, allowing analysts to focus on the key step of identifying threats. With the increasing persistence of real-time, multi-sensor surveillance capabilities there is a natural exploitation route into areas such as ISR, cyber, social monitoring, big data and smart cities. The context-driven approaches developed under the UDRC phase 2 are relevant to the analysis of large volumes of data where targets are seeking to hide their presence within a benign population. The driver here is to identify those behaviours which are not representative of normality and cannot be fully explained by background understanding. This applies to persistent monitoring scenarios and has a strong link with the work on sensor management detailed in chapter 4.

Autonomy is an important exploitation route for context-driven behaviour monitoring and anomaly detection. Future autonomous systems will need to be able to derive their own understanding of the world, observing and responding to the local signals and context in order to provide a capability which can adapt to different operational environments. Without the ability to modify their own behaviour detection, the situation awareness of autonomous systems is likely to be significantly degraded.

5.2.2 Visual features for improved behaviour-based target tracking

Video target tracking algorithms are fundamental to a wide range of defence and civilian applications, including automated surveillance, traffic monitoring, human-computer interaction and virtual reality. Existing algorithms tend to consider targets as point processes (see e.g. the PHD filter [19]), or as re-identifiable objects following known (e.g. Kalman filter [20]) or unknown motion models (e.g. mean-shift [21]). These approaches, however, ignore the richness in video data, which contains other features and context with the potential to vastly reduce computational requirements. For example, pedestrians tend to exhibit ad hoc obstacle avoidance behaviour but to model all possible motion eventualities has high model complexity. In the Kalman filter, for example, tracking error will increase when rapid changes in target motion occur, which in dense scenes increases the possibility of data association errors. In such cases some prior information – a so-called *intentional prior* (e.g. a detected feature, such as the direction in which a pedestrian is looking) that could be used to predict a change in motion, is appealing.

Automatic head pose, or gaze direction, estimation has become an important feature in applications of computer vision to surveillance of human behaviour, with significant works dedicated to head pose extraction from low-resolution surveillance video [22], [23]. These current methods rely on motion priors to smooth head pose estimates, assuming a person's head points

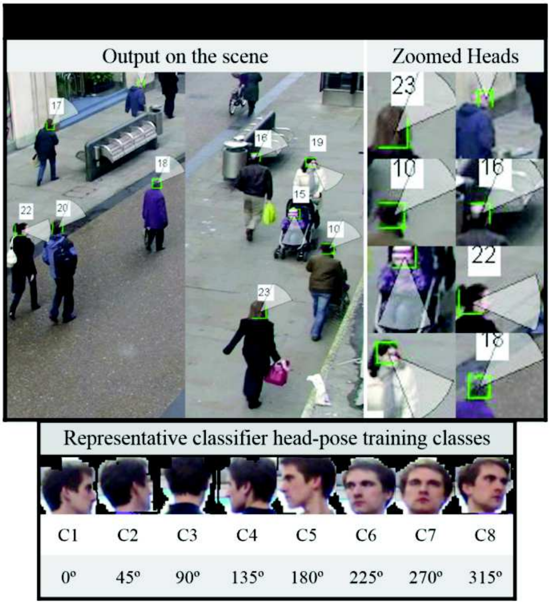

Figure 5.3: Examples of pedestrian head pose on a benchmark surveillance dataset. The head pose has been classified into 8 directions and is used as a contextual signal to inform an intentional prior which enhances tracking performance.

in the direction that they walk, rather than vice versa, which reduces the information potential of this rich visual feature.

Deep learning is a relatively new area of machine learning that replaces hand-crafted features with efficient algorithms for unsupervised hierarchical feature extraction. Key to its success is its ability to learn concepts at different levels of abstraction. The most useful features are automatically identified and used for learning higher-level concepts, from which a robust classifier can then be learnt using a final stage of supervised learning.

Novel work under the UDRC has demonstrated that Deep Belief Networks (DBNs) – a form of deep learning – can discriminate between head pose angles without utilising motion priors [22]. UDRC researchers demonstrated that integrating head pose as an intentional prior improves tracking performance (see figure 5.3). The greatest benefits were observed when tracking targets through occlusions, where predictions based on a target's last observed head pose were found to be significantly more reliable than approaches which don't take into account this additional context. More recent UDRC research on deep learning has shown that head pose based intentional priors can be robustly extracted from video data – even in low resolution surveillance data – and used to improve pedestrian target tracking [22], [23].

More broadly, intentional priors can be considered a special case of behaviour based tracking, feeding back information about how a target is behaving to improve the underlying target tracking. Other examples exist. For coastal surveillance applications the search and mapping strategies of AUVs could be improved. Better operating formations (e.g. bounding overwatch) could aid infantry tracking in complex urban environments.

5.2.3 Developing automated anomaly detection for wide area surveillance

One of the key benefits of wide-area visual surveillance is that large areas can be monitored remotely, and this is providing new opportunities for battlefield understanding. With the oncoming prevalence of manned and unmanned aircraft equipped with both high resolution and broad area sensors, the ability to monitor increasingly large areas in great detail brings numerous technical challenges.

Of particular interest to the UDRC has been how wide area surveillance signals can be processed in such a way as to identify salient aspects both online and in real time. For example, existing wide area motion imagery systems are capable of capturing $\sim 200\,\text{Megapixels}\,\text{s}^{-1}$ and may cover areas from $6 - 50$ km^2 at the rate of several Hz [24]. Automated algorithms are crucial in order to reduce analyst information overload. Furthermore, the provision of automated processing paves the way for a pro-active, rather than reactive capability.

Techniques for automated surveillance are often based on anomaly detection algorithms. The key insight behind anomaly detection is that for most surveillance tasks examples of normal behaviour are abundant, while examples of actual events of interest are scarce and hard to define. Anomaly detection tackles these issues by inverting the problem; that is by attempting to model normality, abnormal or anomalous behaviour can be identified by its poor fit to this pattern. Of course, the anomalies detected are only relevant to the underlying model of normal behaviour, and thus only an indicator that this model cannot explain the observations. Whether that anomaly is genuinely interesting or merely dull but infrequent must still be determined. Completely automated surveillance is thus still challenging to achieve. Nevertheless, the ability to filter surveillance data by saliency is an important capability, particularly for wide-area surveillance, where the number of targets under observation could be in the thousands. Any algorithm that can produce a significant reduction in the number of candidate threats offers clear potential for reducing information overload.

Phase 2 of the UDRC has considered many of these problems in the context of WAMI surveillance (see figure 5.4). A key principle of the UDRC approach is that normal behaviour can rarely be modelled globally, and thus both spatial and temporal context are of high importance. At the spatial level, trajectory clustering techniques inspired by [26] and [27] have been developed to model targets. The vast quantity of observed data is ‘wrapped up’ into more compact distributions representing unique trajectories. Not only can target behaviour be matched to existing clusters in real time, but online learning is also performed allowing the underlying model to be refined and adapted in response to changing scene behaviour.

Many environments are too complex to be modelled using spatial context alone. When, as well as where, target activity normally occurs is important. Using kernel density estimation

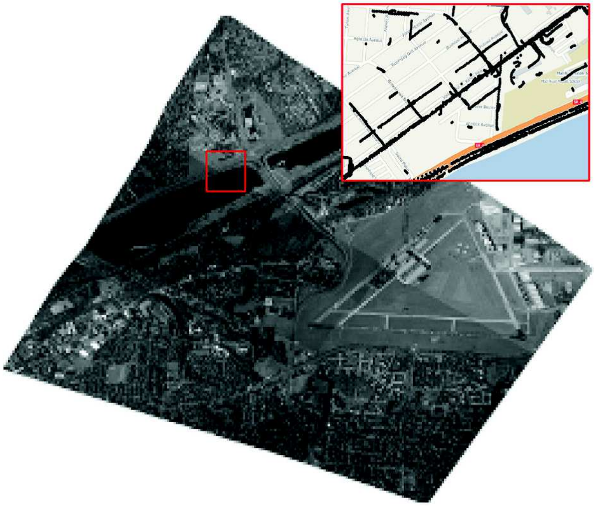

Figure 5.4: A snapshot from the US AFRL WAMI data set from the Wright-Patterson Air Force base. Patterns of behaviour derived from object detection and tracking in the red box are shown in the inset, top right. The data is available publicly from [25].

techniques adapted from [28] temporal activity distributions can be learnt for each spatial cluster in a highly scalable way, suitable for an online, persistent surveillance platform.

Combining these techniques has provided a real-time and online anomaly detection algorithm that is capable of learning from, and detecting anomalies within, large streaming datasets such as WAMI. Moreover, this work provided the first algorithm able to learn spatio-temporal motion patterns over large areas, making it suitable not only for anomaly detection of land, sea and air targets, but also capable of mapping activity in unknown regions.

5.2.4 A deep learning strategy for wide-area surveillance

In the technical literature there are currently no methods that can effectively solve the tracking across cameras problem and therefore enable the design of reliable and affordable surveillance systems. There is a substantial gap between research related to re-identification frameworks and the requirements for real world deployable re-identification systems [29].

The UDRC has considered wide area surveillance networks with unknown, unconstrained topologies and non-calibrated cameras. One of the main unsolved issues in this context is the problem of long-duration occlusion of targets. This is a challenging problem because it combines several non-trivial subproblems [30] such as variation in lighting and pose, changing viewpoint, camera settings, background clutter and imperfect pedestrian detection [31].

The above aspects negatively affect a tracking system on different levels, from detection to the ability to accurately re-identify unique targets from one camera view to another. Many popular approaches to multiple-entity tracking are based on dynamical models or multiple-hypothesis projections. UDRC researchers have developed a cross camera tracking method relying only on re-identification performed by a sub-system (tracklet association) with high-quality feature extraction capability.

Current data-driven state-of-the-art re-identification architectures are limited because they are static, meaning that they stop learning after their training phase. This does not take into consideration the realistic and very likely possibility that the environment where the learning machine is deployed evolves: for example the sensor spatial distribution may change but the re-identification algorithm would retain the old view of the network of cameras. Making a deep architecture context aware by changing according to the variable network statistics can achieve better re-identification. The motivation for the UDRC research comes from the practical need to operate over large areas where dense, complete sensor coverage is infeasible.

The UDRC has developed a unified framework to tackle the long occlusion problem, generating trajectories and using a deep-learning-based re-identification scheme. An iterative adaptive interaction is created between the tasks of tracklet building and re-identification, the effect of which is to boost both steps, thus improving tracking ability when targets disappear. The reason for using deep learning is that, aside from early techniques relying on hand-crafted features [32] or cross-camera transformations [26], it is the only method which has shown an ability to learn complex discriminative mappings that generalise well [33]–[36]. The following advantages of the proposed unified framework have been identified:

- topology independence: the progressive estimation of the network distributions based on the output tracks allows the estimation of unknown, unconstrained topology;
- unsupervised learning of the spatial-temporal relationships of the network;
- fault tolerant behaviour;
- context-awareness, incremental learning of network statistics, and adaptive classification performance;
- modularity, allowing improved algorithms to be integrated as they are developed;
- flexibility, allowing the integration with any dynamic model for intra-view tracking.

Re-identification decisions taken by a deep learning convolutional neural network[1] (CNN), applied on image pairs, can

[1] Convolutional neural networks are a class of deep neural networks that have been demonstrated to be well adapted to object classification in imagery.

benefit from the extra information coming from network context. Network context provides information related to the distribution of transition probabilities for entities moving between camera views within the sparse network. The network context information can be used to condition the CNN, incorporating the additional information to enhance re-identification performance.

More accurate re-identification, in turn, will enable production of less sparse and more reliable trajectories which will be used to improve the estimated network distribution. This cycle incrementally refines at each iteration. At each new re-identification step, the information coming from the predicted track patterns combines with and conditions the information coming from each re-identification.

The UDRC methods propagate probabilities backwards through the layers of the network, using a fast gradient technique, to encode additional environmental awareness into the weights of the CNN. This means the CNN will progressively adapt itself to take into account the current spatio-temporal distribution of cameras. This is a significant difference from existing CNNs which are static after they have been trained.

The overall system is set to have the re-identification module initially bootstrapped to the track building process. That is, an adaptive boosting mechanism where the CNN output forms an informative input in the next iteration. By iterating, the whole process of trajectory extraction is more likely to converge to the ground truth. One fundamental step toward a workable solution is to ensure that the re-identification module is highly accurate, relying initially only on appearance based re-identification.

Taking inspiration from [37] UDRC researchers identified the opportunity to improve the current state of the art of re-identification CNNs, mitigating the problem of the changing camera viewpoint. This is particularly severe in outdoor networks with multiple disjoint cameras. A direct effect of the viewpoint variability is that, in feature space, a pair of images

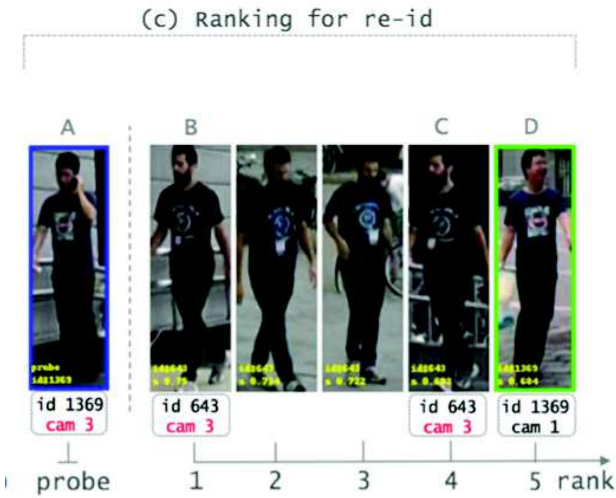

Figure 5.5: The use of the modified loss function during CNN training provides a more discriminative feature space and enhances performance for re-identification across cameras. Using a standard approach the test image A is incorrectly associated with image B and C due to the similar viewpoint. The UDRC technique correctly re-identifies the person in image A as the person in image D.

of the same person shot by different cameras may appear more distinct from each other than a pair of images of different individuals captured by the same camera (see e.g. figure 5.5). To tackle this problem, a state-of-the-art CNN [38], was trained using a new loss function that jointly increases the inter-class discriminative power of the deep features and their intra-class compactness.

Compared to metric learning techniques like the joint Bayesian scheme [39] the UDRC approach shows a bigger improvement over the Euclidean distance baseline. This is because the UDRC approach influences the building of the feature space instead of merely learning a function over it after the CNN weights have been computed. On two of the largest image-based datasets for person re-identification, CUHK03 [40] and Market-1501 [35] the

UDRC methods improve the state-of-the-art.

5.2.5 Multi-spectral single photon counting lidar

This work focusses on signal processing and algorithm development for penetrative sensing using full-waveform light detection and ranging (FW-lidar). Discrete return lidar systems provide a series of echoes that reflect from objects in a scene. In contrast FW-lidar systems measure the intensity of a laser light reflected from objects continuously over a period. Measurements made at different wavelengths provide a multi- or hyper-spectral lidar (MSL) data set. See figure 5.6 for a schematic. Targets have different spectral reflectance due to their geometry and chemical composition. FW-MSL measurements thus provide highly distinguishable target information. Extracting this information by processing FW-MSL is challenging, however. Involved processing is required to convert such measurements to 3D point clouds which reveal spatial distribution, and the material identification provided by spectra. As the computational complexity of the solutions is necessarily high, the UDRC research looks to develop effective and fast approaches which use intelligent resource allocation. The algorithms produced are divided into two types.

1. Those which find abnormal regions in large lidar datasets (fast anomaly detection). The aim here is to process the raw FW-MSL measurements (photon counts) to detect spectral anomalies. This is a precursor to finding interesting signals, worthy of more detailed sampling and analysis to detect man-made objects, e.g. vehicles under foliage, or mines underwater.

2. Those which characterise structure in anomalous regions (peak modelling and discrimination). More complex algorithms have been developed to convert FW-MSL signals into 3D point cloud data which reveal hidden structure.

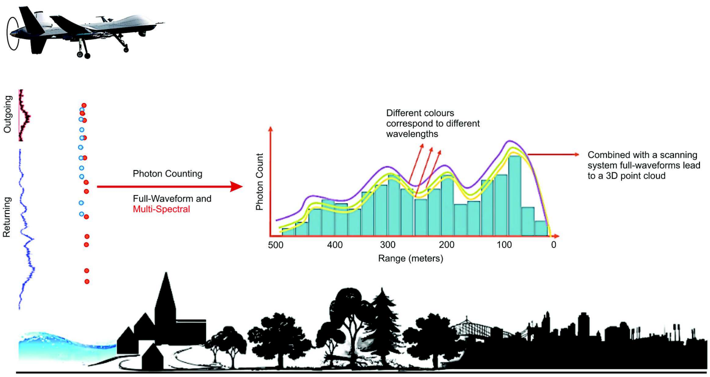

Figure 5.6: Operational principle & scenario for single photon counting sensing

Anomaly detection and classification in aerial laser scanning data

Research has been conducted to detect spectral and temporal anomalies in FW-MSL data samples. An anomaly is defined as a full waveform temporal and spectral signature that does not conform to a prior expectation, represented using a learnt subspace (a dictionary) and set of coefficients that capture co-occurring local-patterns using an overlapping temporal window. An optimisation scheme has been proposed for subspace learning based on stochastic approximations. The reward function is augmented with a discriminative term that represents the subspace's separability properties and supports anomaly characterisation. The algorithm detects man-made objects hidden in dense vegetation and allows tree species classification [41].

The 3D points in figure 5.7 are extracted from photon histograms. The UDRC algorithm, called SPeED [42], not only extracts peaks but classifies them simultaneously. The results are compared with the approach in [43], which is robust to

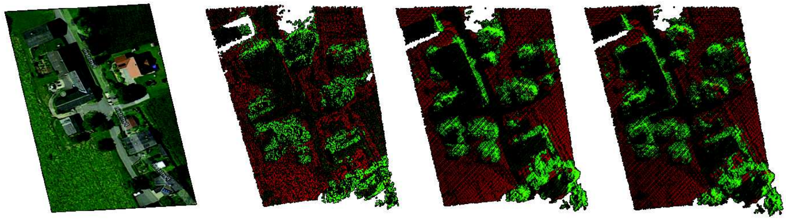

Figure 5.7: Results from a classification of the ground surface into vegetation and man-made objects (houses, roads, tarmac) using spectral and geometric properties of the multi-spectral lidar. Left to right: region scanned as part of aerial trial; classification result at 1550nm; result at 1064nm and (right) combined multi-spectral result.

noise but is not suitable for practical applications due to its time complexity. This was addressed in [44] but parameter tuning makes that a less attractive proposition. The SPeED algorithm, on the other hand, improves the true positive rate by a factor of 1.4 and shows a two-hundredfold decrease in computational time when processing an individual waveform.

Underwater single photon counting

The focus for the second type of algorithm was on processing underwater lidar measurements [45] and developing algorithms that simultaneously detect and classify peaks in FW-MSL data. Here the key has been to combine geometric and spectral features; fast non-linear sparse representation is learnt for signal characterisation [46], [47].

A novel, highly discriminative spectral-depth representation was developed to characterise different target signatures underwater. Several custom made realistically scaled examples of known and unknown targets have been investigated using the FW-MSL system [45]. Using the proposed spectral depth representation, sparse codes are optimised for maximum discrimination between different materials and mines, demonstrating classification accuracies of 97.8% and 98.7%, respectively.

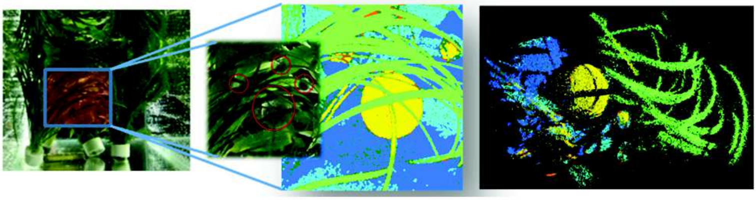

Figure 5.8: Underwater experiment with targets detected behind foliage. Left: original image, middle: inset segmented into different target types, right: 3D reconstruction and object classification. Targets are colour coded for purposes of illustration.

Combining depth with spectral data, the approach is very effective at discriminating targets of different shapes, but with similar spectral response, or conversely of similar shape but having different spectra (see figure 5.8). This work has been the first to report the analysis and discrimination of multi-spectral underwater single photon counting lidar signals as an alternative to acoustic mine countermeasures.

5.3 Automated statistical anomaly detection and incongruence determination

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The problem of anomaly detection in machine perception has received substantial interest over the last decade. As the notion of an anomaly depends on the user and context, various systems with different perspectives have been proposed to address this problem. Conventionally, an anomaly is defined as an outlier from some known distribution [48], [49] and classical approaches that adhere to this view have been summarised in surveys such as [50]–[53]. The applications described in this section rely on fundamental research into incongruence measures developed under UDRC phase 2 [54]–[57].

5.3.1 Anomaly detection in tracks from shipping

UDRC researchers developed their incongruence detection methods and adapted them for the automatic detection of anomalous shipping tracks. Maritime anomaly detection is an important aspect of maintaining a recognised maritime picture as it aids sea traffic control and collision avoidance. It also contributes to navigation surveillance and detection of illegal marine activity such as piracy, drug smuggling or terrorism. In this study, the UDRC concentrated on the case of detecting anomalous shipping tracks traced by ferries, by using shipping data collected via Automatic Identification System (AIS) messaging, though the method is generally applicable to any large database of tracks. AIS reporting is compulsory for ships over 300 tonnes[2] and provides information about position along with other details to aid identification. It is important to note that although the AIS messages can be transmitted every second, due to the vagaries of the system (such as faulty or incorrectly programmed equipment), rules mandating different transmission rates in different locations (e.g. more reporting in ports and congested seaways) and environmental effects affecting range and background noise, the data received is almost

[2] In this case computed by way of *gross tonnage* which is actually a measure of internal volume rather than mass.

never complete or synchronised. The UDRC-developed methods cope with the messy and incomplete nature of AIS data. The particular data used in this case was collected by Thales UK in the Solent area between July and August 2012, and consists of various vessels occupying the region of interest. Ferries were selected from this data to more easily prove the method.

The method used displacement information (i.e. location), and vessel direction (heading). Gaussian processes (GPs), a flexible machine learning method for regression and classification, was used to model the distance function over the normalised duration of a single trip between two ports. The approach differs from a recent study [58] in terms of exploiting overall trip duration in addition to velocity during regression. Another novelty presented in this work was the use of a 'data-cleansing system', where unlabelled training data, which may be corrupted by anomalies, is cleansed of outliers by using a median absolute deviation method based on time grids, prior to GP modelling. This allows the use of training data without making unrealistic assumptions about the reliability of AIS records.

In addition to the displacement of a vessel normalised over time within a single trip, the UDRC approach uses the direction of travel at a given location. For this, a second set of outlier detectors utilise spatial grids superimposed on the region of interest and model heading information by employing Markov chains. The final combination is then obtained by fusing the decisions of the two classifiers such that if either of the classifiers detects a test track as anomalous, then it is taken as anomalous.

The performance of the proposed approach is assessed by way of the tracks that are classified as anomalous as a function of those that are labelled normal by the algorithm. The results are presented in figure 5.9 for an example test set; the tracks labelled anomalous are shown as darker lines against the normal tracks in a lighter colour. A 93% detection rate for anomalies with 2% false positive rate (FPR) is obtained. It is possible to

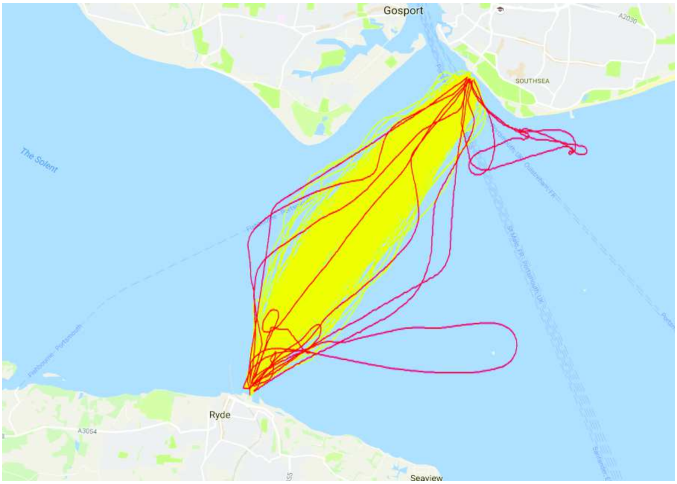

Figure 5.9: Smoothed spatial distribution of a set of ferry tracks (yellow). Anomalies identified by the UDRC method are shown in red.

detect all anomalies with FPR=6%. Anomalies can be detected in speed and heading as well as in location.

Further improvements on the algorithm are to be carried out by considering different kernels for the GP regression. Kernels are functions which represent the correlation between points in the native space of the measurement, and so a kernel tuned to vessel behaviour will better fit the problem and provide higher discriminative ability. The current model tests a completed ferry trip for anomaly detection, whereas an online detection framework is to be developed for real-time detection of anomalous behaviour. Also, use of feature parameters over and above location, heading and speed is to be tested.

5.3.2 Activity recognition and anomaly detection in video

The recognition of human activities and the discovery of anomalous behaviour in video is an important research topic, with

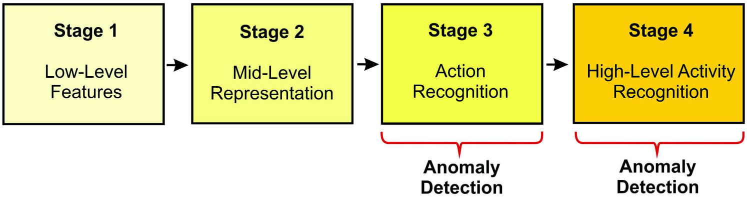

Figure 5.10: The system proposed for human action and activity recognition and anomaly detection in video.

many applications in the fields of surveillance, security and digital media. Modern ISR platforms generate many more still and moving images than can be viewed, analysed and interpreted by human operators, so potentially useful intelligence can be missed. Consequently there is a need for automated interpretation of video to track people and vehicles and to recognise and detect behaviour associated with threats. UDRC researchers have developed a workflow that combines several established and novel techniques for activity recognition in video at increasing levels of abstraction, resulting in improved results in automated interpretation of video.

This section describes the resulting system. It comprises four steps: (i) extraction of low-level features from the input stream; (ii) efficient mid-level representation of the extracted features; (iii) action recognition; (iv) high-level activity recognition (see figure 5.10). Each of these steps is outlined in the following paragraphs.

Feature extraction

There are currently three main approaches to feature extraction from video footage.

1. Objects of interest in a scene are detected and tracked; then their tracks are analysed to understand activities

(e.g. [59]).

2. Use of hand-crafted local space-time feature vectors (e.g. [60], [61]).
3. Features are learnt from data using machine learning approaches, of which deep learning variants (e.g. [62], [63]) have gained a lot of recent interest.

When solving an activity recognition problem all available approaches have strengths and weaknesses. The object detection approach can simplify the activity recognition problem into one of trajectory analysis. However, clutter and occlusions are likely to obscure detections and there are cases when it is uncertain what the object of interest is and what it looks like. Moreover, the method's efficiency relies on the performance of the object tracker.

Local space-time features utilise manually-defined descriptors and have the advantage of encoding motion and appearance without the need for object detection. On the other hand, they typically produce high-dimensional data which impose a significant computational burden.

So-called deep features are learnt automatically from videos and thus alleviate the need for manually defined descriptors. However, a large amount of training data are required for this method to work robustly.

In the context of defence applications two canonical examples are instructive.

- Wide area surveillance (e.g. WAMI datasets such as [25]), where large numbers of targets (> 500) are observed simultaneously. Given that the target type is known, their shapes are similar and their trajectories are normally constrained (as they follow a road structure), there exist reliable systems for target detection and tracking. This is a trajectory analysis problem.

- Close-up surveillance (e.g. FMV), where one or more targets (typically ≤ 10) are present at a given time. In this case, activity recognition involves the detection of internal motion of the targets, such as gestures or facial expressions. This task can be aided by the derivation of local spatio-temporal features. Machine learning can also be used if a large amount of training data are available. When multiple targets are present, a hybrid approach can be adopted, i.e. first detect the targets and then extract local features from the detection windows. This eases the computational burden as it limits the feature extraction area.

Mid-level representation

Recent work has shown that pooling techniques, such as bags-of-features and Fisher vectors [64] can enhance the performance of various feature types. Pooling can solve practical problems, e.g. handling vectors of different length (often occurring in trajectory analysis) or discovering underlying structures in the data.

Action recognition

Action recognition is achieved by classifying the results of the mid-level representation stage. Prominent choices for this stage are SVMs [65] and random forests (RFs) [66] for supervised classification (when training data are available), k-means and Gaussian mixture models for unsupervised classification and Hidden Markov models (HMMs) [67] and their variants, when there are temporal dependencies in the data.

High-level activity recognition

An activity is typically represented as a sequence of its constituent actions. Most activity analysis frameworks developed to date focus on relatively simple tasks. Algorithms for more complicated activities have been proposed in [68] and more recently in [69]. Both of these methods assume that the structure of the modelled activities is given *a priori* by experts. Although this is a reasonable assumption when considering complicated activities, automatic learning of the model's structure is a desirable property, as the variability in task execution may render the task of manual structure definition overly time consuming. Additionally, model-based methods rely on accurate recognition of an activity's constituent actions.

To address the shortcomings of previous approaches, UDRC researchers proposed a new algorithm for activity recognition in [70]. It can model activities whose exact structure is not previously known. It is capable of efficiently representing the natural hierarchy of complex activities and encoding the temporal relations between their constituent actions. The algorithm combines a discriminative feature classifier based on RFs and a generative classifier for temporal analysis, for which a hierarchical HMM is used [71]. The discriminative feature facility checks the existence or absence of the steps required for the execution of an activity, while the generative model encodes the ordering of these steps. The UDRC algorithm can be applied to any task which involves complex activities, as all of its components are learnt automatically from training data.

The proposed algorithm can be used to detect parts of activities which are erroneous or anomalous. When such proto-activities are present in the training dataset, this is achieved by building separate model parts corresponding to the erroneous aspects. In the absence of such data, the UDRC-developed method can detect anomalies by assessing the confidence scores assigned to various parts of activities during the classification process [55].

Applications to WAMI and FMV

For the problem of wide area surveillance the Wright Patterson Air Force Base 2009 WAMI dataset [25] has been processed. In

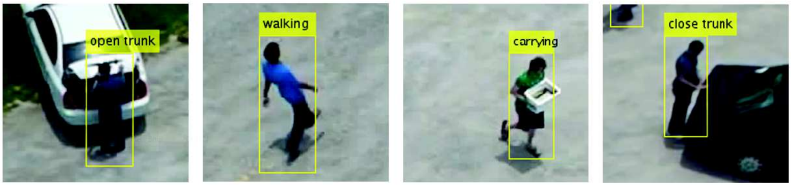

Figure 5.11: Examples of actions detected by the UDRC-developed action recognition algorithm on FMV data

these data, trajectories from a vehicle detection and tracking algorithm were provided. For the mid-level representation, a grid was placed on the area of interest and the trajectories were converted to vectors of equal length with the bag-of-words algorithm.

FMV footage is available as part of the WASABI dataset [72] and the public UCF-ARG dataset [73]. For these data, action recognition was performed as follows: (i) humans in the scene were detected with the Faster R-CNN deep learning detector [74] which was trained with 4000 samples, (ii) action recognition was achieved in a supervised manner with the temporal segment network (TSN) deep learning framework [62]. TSNs extract low-level deep features based on motion and appearance and the mid-level representation was acquired by feature pooling. Finally, the assignment of input data to classes, representing human actions, was achieved by performing average pooling and a softmax activation on a fully connected layer. The action recognition facility was complemented with an action recognition component based on handcrafted features extracted with the improved dense trajectories method [60] to augment the system's performance. Examples of actions detected by the system are shown in figure 5.11.

UDRC researchers have also worked with the publicly available *Breakfast dataset* [75] to demonstrate complex action and activity recognition from videos. In this dataset the goal is twofold: first, to recognise simple actions (such as cut fruit, take bowl); second, to recognise high level, complex activities (such as prepare salad) by utilising the detected actions. The Breakfast dataset poses several challenges. It comprises a large number of videos (∼1700) and the temporal localisation and recognition of actions is hard due to the variety of environments, camera angles and participants.

To detect actions from video, low-level local features were first extracted with improved dense trajectories [60] and Fisher vectors were used for the mid-level representation. Action recognition and temporal localisation was performed with HMMs implemented with the HTK toolkit [76]. Finally, the UDRC algorithm from [70] was used for activity recognition. It provides temporal extent for each detected action (i.e. its start and end point within the video), class (e.g. pour water, stir milk) and a detection score. The HTK toolkit was used to build two classifiers: a contextual classifier, which performs recognition by utilising information regarding each action's neighbouring actions, and a non-contextual classifier which performs action recognition without considering neighbours.

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Chapter 6

Implementation

This chapter explores efficient practical design and implementation of signal processing algorithms. In academic literature on signal processing, the focus is on powerful algorithms that provide high performance, but typically at the cost of increasing complexity. In practical implementations, the limiting factor of algorithm complexity must be borne in mind. System designers need to find approaches that are capable of providing acceptable performance within the limits of hardware and software platforms. The UDRC has explored these issues in detail, addressing the trade-off between system performance and the complexity and processing capabilities of the device or network being used.

The development of low-complexity algorithms for efficient processing of high-dimensional data is important in many domains (e.g. array processing in radar or sonar, or pattern recognition in large data). Through the development of lower dimensional representations the UDRC has made gains in reducing the computational cost of key signal processing tasks. The associated algorithm performance increase and more efficient data representation can provide a means to develop processing systems that operate on smaller and lighter processing platforms.

6.1 Low-complexity algorithms and efficient implementation

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In recent years the potential for so-called *polynomial matrix*[1] algorithms to provide elegant solutions for broadband sensor array processing problems has become widely accepted. The UDRC has further contributed to the state of the art by increasing the computational efficiency of these algorithms. These improvements are now being implemented on hardware to allow high-performance broadband processing to be undertaken on low-power systems, deployable on lightweight and mobile platforms.

For some time now radar and sonar users have benefited from narrowband[2] sensor array processing to estimate threat bearings (i.e. DOA), form beams, mitigate interference and

[1] A polynomial matrix is a generalisation of a scalar matrix in which each element is represented as a polynomial function. They can be used to extend matrix representations to higher-dimensional data.

[2] When a sensor is sensitive only to a very limited range in frequency, algorithms can assume that all signal power exists at a single frequency. This simplifies their derivation somewhat.

counter jamming. Despite the fact that processing requirements are computationally demanding and application extensions to portable or autonomous systems have been challenging, several mature methods exist [1].

The switch from narrowband processing to broadband is not straightforward (see §2.2) and this has discouraged users from exploiting the rich source of information obtainable through broadband array signal processing. Chapter 2 described how the UDRC research has addressed the signal processing requirements for a broadband sensor system. Polynomial matrix representations, pioneered by the UDRC research team, have enabled the narrowband problem to be transformed into a broadband problem in a robust way. In addition, UDRC researchers have adapted the algorithms with the aim of implementing these on platforms with low SWAP. This is extremely pertinent to processing requirements for autonomous platforms (e.g. UAVs) and man-portable systems. The development of low-complexity algorithms has brought the exploitation of this technology into scope for military systems designers. An example of this is the performance gains seen in sonar array applications.

The development of field programmable gate array (FPGA) technology has made the implementation of polynomial matrix algorithms on low-SWAP platforms achievable at a reasonable cost. An FPGA is a programmable integrated circuit device that allows any circuit (derived from an algorithm) to be implemented in custom hardware. FPGAs are especially suitable for low production volume electronic systems typical of those found in defence. They enable very fast, highly parallel processing, as separate dedicated hardware can be used to calculate different parts of an algorithm. They are made up of banks of programmable logic (a blank slate) on which the circuit design is synthesised, along with dedicated fast multiplier blocks, fast block RAM memory, and assorted interfaces and peripherals. They consume relatively little power, with power usage scaling linearly with the amount of programmable logic utilised by the design on the device. As the FPGA is reconfigurable, a variety of test designs can be explored using the same device, and the design may also be updated to improve performance and include new features.

6.1.1 Broadband sensor array processing with polynomial matrix representations

Sensor arrays form the basis for an increasingly wide variety of applications, including MIMO communications, radar and sonar systems, and are concerned with gathering and combining data from a collection of sensors to perform estimation of signal and environmental parameters through spatial and temporal processing (see e.g. chapters 2 and 3). The incoming signal data can be formed into measurement, analysis and steering vectors, allowing signal data from neighbouring sensors, and previous time intervals to be compared through the computation of a covariance matrix. This covariance matrix captures correlations within the data (and also at multiple time instances), allowing underlying information about the environment and scenario to be extracted through application of linear signal processing techniques.

Matrix decomposition techniques, where a large matrix can be broken down to reveal the dominant contributing factors, are especially important in this field. In particular, eigenvalue decompositions (EVDs), have proven optimal for many narrowband problems. EVD allows a Hermitian matrix (a square matrix of complex numbers, with the symmetric property that it is equal to its conjugate transpose) to be factorised [2]. Such a factorisation allows subspace decompositions to be revealed that are useful in data compression and DOA applications. In the narrowband case, the propagation delay characterised by signals travelling across the sensor array can be modelled sufficiently as a phase shift between the signals detected. However, in the broadband case this method no longer holds. Instead, the scenario may be modelled using time delays between the signals detected at multiple array sensor elements.

In recent years, researchers have sought to develop new techniques for tackling broadband sensor array processing. The UDRC has investigated the use of polynomial matrix techniques to tackle this objective, as these representations provide an elegant representation of the data which has greater flexibility and allows full time delays to be modelled rather than just phase shifts. Traditional broadband processing techniques have typically adopted a *divide-and-conquer* approach where the spectrum of interest is divided into multiple frequency bins before established narrowband techniques are applied. This may lead to a lack of coherence or discontinuities in results computed as a function of frequency.

6.1.2 Improving the computational efficiency of PEVD algorithms

The foundation of the research conducted by the UDRC during phase 2 has been the development of new, more computationally efficient, iterative polynomial eigenvalue decomposition (PEVD) algorithms [3]. PEVD algorithms are an extension of classic EVD algorithms to the case of polynomial matrices. The EVD is a powerful tool for factorising Hermitian matrices, and is widely-used in array processing problems to reveal subspace decompositions. The research conducted by the UDRC resulted in PEVD algorithms that offer better computational performance (in terms of diagonalisation of the matrix) in both reduced execution time and a lower number of iterations required to reach the same threshold [4]. Furthermore, the new algorithms have delivered benefits by reducing the order of the matrices that are returned. This is especially important if the decomposition is ultimately to be deployed in hardware. Further refinements include a divide-and-conquer scheme for tackling large matrix problems [5], more efficient restricted matrix element search spaces, integration of approximate EVD methods, and truncation methods. These have offered notable computational improvements.

A number of different iterative PEVD algorithms have been developed under the UDRC phase 2, including *sequential-matrix-decomposition* (SMD) [4], and *multiple-shift SMD* [6], which build on the *second-order sequential best rotation* (SBR2) algorithm [3], the progenitor of this new body of work. The newer SMD family of algorithms allows diagonalisation to a much greater degree than the original SBR2 algorithm. The SMD algorithms achieve this by transferring more energy per iteration from the off-diagonal elements. This has been shown to lead to a significant increase in performance of the resultant algorithm in terms of convergence. In addition to greater diagonalisation performance, the SMD algorithms also allow the order of the output matrices to be constrained relative to the original SBR2 algorithm. This is important for practical hardware implementation.

The SMD algorithms are more complex to calculate than the SBR2 owing to a full EVD operation being required on each iteration of the algorithm. Therefore, further developments have been made to address this complexity by employing EVD approximation methods including cyclic-by-row rotations [7], and new truncation methods [8] to restrict growth in the length of the output matrices. These developments have allowed the greater diagonalisation power of the SMD methods to become competitive with the simpler SBR2 methods in terms of computational complexity.

An important aspect of the work on polynomial matrix techniques has been the development of the divide-and-conquer SMD approach for tackling larger-scale problems. The PEVD algorithms operate on a space-time covariance matrix that is estimated through computing the correlation of sensor array inputs, where the number of sensor inputs (N) dictates the size of the matrix to be decomposed ($N \times N$). Therefore, for large arrays of sensors (such as those found in sonar applications) this will result in very large data structures. Furthermore, the potential for partitioning of data to perform parallel processing is non-trivial. This restriction has motivated a new strategy for exploitation of the algorithms in custom parallel hardware, where large matrices can be first be divided, before a PEVD algorithm can be applied (the conquer step) in parallel (i.e. using multiple PEVD threads).

6.1.3 Practical realisations of PEVD

In order to demonstrate the potential utility of the new more powerful polynomial matrix algorithms, a number of applications of these methods have been considered. Two important topics in sensor array processing are DOA and beamforming [1]. DOA estimation is a well-established problem where the direction of unknown signal sources must be determined from analysis of signals propagating across array elements. Such information is of great importance in analysing the nature of the environment. Beamforming is a spatial filtering technique used to determine the optimal directivity of an array of sensors to facilitate either the transmission, or reception of a signal (c.f. §2.2). Beamforming can loosely be understood as the inverse of DOA determination, where instead of finding the angle of an incoming signal, the desire is to optimise the power of the transmission to a particular angle, or to maximize the reception of a signal at an angle of interest, or even to block it out by null-pointing. All of this is achieved by forming beams through constructive interference of the contributions from individual sensor array elements. For both these applications, the research conducted by UDRC during phase 2 has sought to leverage the added flexibility of the polynomial matrix algorithms to deliver broadband solutions.

In addition to applications for polynomial matrix algorithms, UDRC researchers have investigated how these algorithms should be adapted for implementation on FPGA hardware. The work carried out by UDRC researchers has shown how the PEVD algorithms can be implemented on an FPGA device, and how the algorithm can both be computed and accelerated on a low-

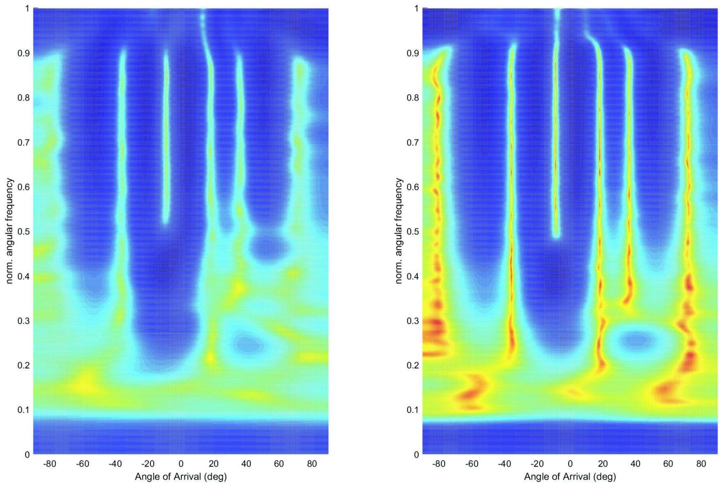

Figure 6.1: Broadband angle of arrival estimation with polynomial MUSIC algorithms, using SBR2 (left) and SMD (right). The more powerful diagonalisation performance of SMD, evident by way of the stronger linear features on the right, leads to better estimation resolution for the same computational cost.

power device.

Multiple signal classification (MUSIC) [9] is a well-established and powerful algorithm used for the estimation of frequency and emitter DOA. Various methods have been proposed to extend the original MUSIC algorithm from narrowband to broadband problems [10]. A notable such approach is the *coherent signal subspace* (CSS) [11] method, which transforms the broadband problem into a narrowband one, through the use of focussing matrices to appropriately align covariance matrices across narrowband frequency bins. The focussing matrices of the CSS approach pre-steers (from approximate knowledge) the array data so that the sources of interest appear in the vicinity of the array's broadside, where array response vectors for

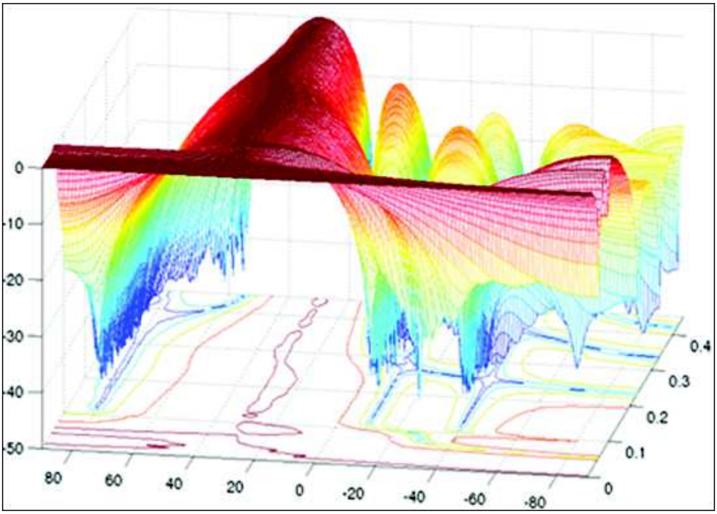

Figure 6.2: Broadband beamforming with a polynomial matrix-based Capon beamformer. The axes show angle in degrees (cross range) and normalised frequency (down range). The z-axis shows the logarithmic gain, measured in decibels. This solution shows good main-lobe response as well as sidelobe suppression over a range of frequencies.

all temporal frequencies approximately coincide. In contrast to this approach, the UDRC developed a polynomial MUSIC approach using polynomial space-time covariance matrices [10], [12], an example of which is shown in figure 6.1. The signal subspaces created by iterative PEVD algorithms are exploited by polynomial MUSIC. The subspaces may then be applied directly to the broadband array data, to identify source angles across a broadband frequency range.

Broadband beamforming has also been successfully demonstrated as an application of polynomial matrix factorisations. UDRC researchers have formulated and solved a polynomial matrix-based Capon beamformer [13]–[15]. The gain response of a Capon beamformer design with look direction towards 30 degrees in the presence of three interferers is shown in figure 6.2.

6.1.4 Future PEVD theory and implementation

The polynomial matrix algorithm design and applications have been published in IEEE academic journals and conference proceedings. Furthermore, with support from UDRC industrial partner, The Mathworks, the PEVD algorithms have been made available openly in the first Matlab toolbox for PEVD algorithms. This was first released in late 2014, is available at [16] and is also linked to the Mathworks File Exchange. The FPGA hardware demonstrator is to be published in conference or journal proceedings, with a version taken up by Dstl. Substantial progress is continuing to be made in polynomial matrix algorithm implementation. Enhanced metrics are accuracy and computational speed. The cultivation of new application areas is also being pursued.

Funding from Leonardo has been secured to support a PhD studentship to develop novel techniques for efficient direction of arrival estimation of broadband sources. This will specifically address the computational cost versus accuracy challenges associated with broadband source localisation. The method builds on novel and computational efficient methods for direction of arrival estimation based on polynomial matrices.

The work carried out by the UDRC on polynomial matrix algorithms has successfully addressed a number of problems that had previously been impossible to solve. However, proof of convergence in terms of minimising off-diagonal energy has been difficult to establish. Different algorithms often return different solutions. As a result, recent efforts have focussed on how the existence and uniqueness of the decomposition may be demonstrated. This is of particular value from a theoretical perspective, but has also led to a greater understanding that shall enable the creation of a new family of *parahermitian*, rather than polynomial, matrix EVD algorithms that address the long-standing problems of source permutation in blind source separation.

6.2 Efficient computation of complex signal processing algorithms

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Efficient and robust sensor processing algorithms are required in a range of applications in the military domain. When platforms are distributed across a geographical area (e.g. as in electronic surveillance) issues around the positioning of sensors and the fusion of data arise. In this section, practical implementation constraints are explored in a series of defence-related signal processing problems. Firstly, binary image classification algorithms have been extended to provide a confidence score indicating the reliability of the classifier. Next, a novel low-complexity approach, based on sparse transforms, has been developed and applied to image coding. This has application to a variety of other signal processing problems. Thirdly, UDRC researchers have addressed efficient signal processing in a network of wireless sensors, evaluating how the performance of the network scales with the number of available sensors, and the optimal number of sensors to achieve a desired performance. Finally in this section, the UDRC has evaluated efficient signal processing on FPGAs, showing how performance and resource use of these devices can be traded off against energy consumption. Examples of this type of problem occur in strategic radar and EO sensing. Networks of sensors where reconfiguration, relocation or activation of sensing nodes are considerations for an operator are also avenues for exploitation.

6.2.1 Improving the reliability of image-based object detectors

Object detectors in imagery typically work by processing the pixels within a region of interest in order to extract relevant features including shape, colour or texture. These features can then be classified using a machine learning technique whose number include SVMs, decision trees (e.g. Adaboost) or various deep learning techniques. Learning methods use an object model, learnt during a training phase, which expresses a representation of how the object is expected to appear in the test image. The features calculated from a test sample are then compared to the object model. This produces a yes or no decision about whether the object is present in that region. As well as a binary decision, the classification stage can produce a confidence score. Using additional training samples, this can be converted to a probability value which expresses the classifier's belief that a particular object is present. This allows comparisons between different classifiers to be made, and probabilities of detection can be passed to subsequent algorithms.

Many of the recent advances in detection capability have focused on improving the accuracy of the decision maker, attempting to reduce false positives (background wrongly identified as an object of interest) and false negatives (objects of interest missed). State-of-the-art detectors are generally significantly more confident about the presence or absence of an object in a region than they should be, and areas of significant uncertainty (around 50% probability that an object is present at all) are under-represented. This makes object detectors unreliable; if an autonomous system or human operator depends upon a detector which returns positives (true or false) with

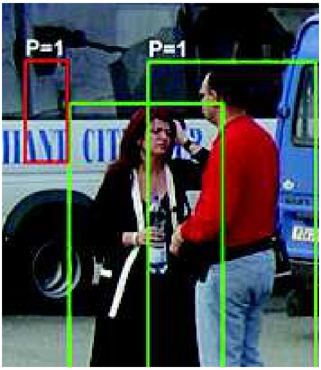

Figure 6.3: An overconfident person detector algorithm. True positives (green boxes) and false positives (red boxes) are both detected with 100% confidence. See [17] for details of the classification algorithms. The image comes from [18].

overconfidence, the subsequent decision will be faulty (see figure 6.3 for an example).

Introspective classifiers which provide both decision information and probabilistic confidence information are particularly useful for data fusion techniques that analyse and combine information from multiple sources [19]. For example, WAMI sensors can provide continuous surveillance data for large areas to look for objects, people, or vehicles of interest. Introspective classifiers can provide a reliability measure to assist higher level data fusion algorithms to assess whether a particular target has been reliably classified in order to make threat assessment decisions. Similarly, in military countermeasure scenarios, reliability estimates can help electronic systems to assess the actual threat posed from a contact received at a particular sensor

The UDRC has developed improved classification techniques based on Gaussian Process classifiers (GPCs). These model the distribution of features in the two classes of interest (object and background) and have been shown to identify ambiguous regions which contain uncertain detections more reliably, while achieving similar levels of accuracy [17]. They also generate probabilistic classifications. However, GPCs require many more computations than equivalent techniques (Adaboost or SVMs). To mitigate this, UDRC researchers first used faster classifiers (Adaboost) to process the whole image to generate preliminary confidence scores. High-scoring regions which may contain objects of interest were then processed with the GPC to generate accurate, reliable detections in a fraction of the time taken to process the entire image. In addition, GPC calculations have been accelerated using GPUs to further reduce processing time [20].

Reliable object detection in video and imagery is a challenge in many military and security applications. Applying a fast and relatively accurate detector (Adaboost) followed by using a slower, more introspective GPC allows a substantially faster detection rate coupled with a significant gain in accuracy, reliability and user transparency. This can be utilised effectively throughout many sensing modalities to perform monitoring or surveillance tasks which rely on object detection.

6.2.2 Learning fast sparsifying transforms

Dictionary learning methods are a class of algorithm that have seen many applications in signal processing; for example, image processing, wireless communications and machine learning. The key idea of this approach is to learn a very specific transform known as an overcomplete dictionary for a particular task, like coding or classification, from the data itself. Such numerically efficient dictionaries are particularly useful in low-SWAP and low-cost implementations. While the dictionary learning problem is computationally complex in general, it has been extensively studied and good algorithms to tackle it exist. Alternating minimisation methods [21] have been shown to work well in practice and also enjoy some theoretical performance guarantees. UDRC researchers have extended this strategy by employing an alternating optimisation procedure. While learn-

Figure 6.4: Fast transforms learnt in an image denoising application. Left: original image, middle: noisy version that has half the pixels removed, right: the reconstruction from the noisy image using the UDRC transforms. (Original image available at [25].)

ing a dictionary they construct two objects: the dictionary and the representation of the data in the dictionary.

Learnt dictionaries with low computational complexity can bridge the gap between the classical transforms preferred in power limited hardware or battery operated devices, and the overcomplete, computationally cumbersome, learnt dictionaries that provide state-of-the-art performance in many machine learning tasks. As an example UDRC developed effective learnt transformations for image coding. They chose to focus on these data since here there are well known transforms (like the discrete cosine transform) that are well suited for natural image representation. The resultant computationally-efficient dictionaries' representation performance sits between that of the classical methods and that of computationally complex learnt dictionaries. Moreover, the UDRC methods are able to build transformations that are simultaneously better (in terms of representation error) and faster (in terms of the number of operations performed) than current methods [22]–[24]. See figure 6.4 for an example of fast transforms applied to an image denoising example. The UDRC method builds very efficient dictionaries that are not orthogonal. The lack of the orthogonal structure leads to more complicated algorithms to compute the change of representation basis of given data.

Future work will take account of the practical difficulties of implementing these algorithms in highly specialised hardware (such as DSP processors or FPGAs). Another line of research is to construct transformations that perform additions and subtractions but no multiplications. This may extend the role of learnt transforms to scenarios where strict hardware and energy consumption constraints are imposed.

6.2.3 Selection and scheduling algorithms for sensor networks

Sensor networks can be extensible and cost effective tools to measure and monitor physical phenomena like the electromagnetic environment or the concentration of pollutants. Modern wireless sensor networks may be composed of a large number of heterogeneous sensors each with its own (possibly limited) power supply capable of performing measurements, processing the result and communicating it to neighbouring sensors in the network.

The UDRC has developed scheduling algorithms based on *convex optimisation relaxations* to construct scheduling schemes for sensor networks composed of power limited, heterogeneous, sensors. They have shown how the algorithms schedule the network and provide theoretical guarantees that describe the estimation accuracy of the network.

An example sensor network with 10 measurement nodes and a master node is shown in figure 6.5 (left). Each node in the network is able to perform a (noisy) measurement at a known cost (measured as energy consumed). The topology of the network imposes strict transmission energy costs (in the example in the figure, data from node 7 is forwarded through nodes 6 and 1 before arriving at the master node). In this scenario the cost of performing the measurement is proportional to the quality of the measurement, as quantified by its SNR. Given these operational costs, the goal has been to schedule the operation of the network over multiple iterations such that the

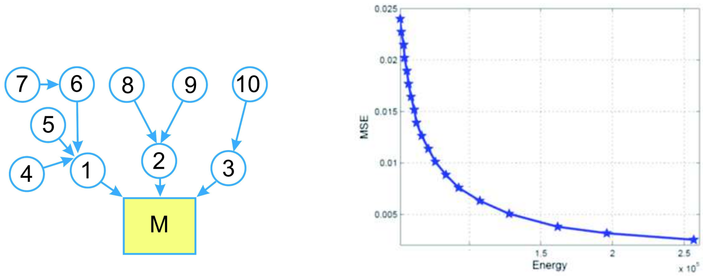

Figure 6.5: Left: network with 10 measurement nodes and a master node (labelled M). Right: trade-off curve for the network showing the relationship between algorithmic error estimate (MSE) and energy consumption (measured in Watts). Increasing the energy on the x-axis implies that more sensor measurements are taken, which reduces the MSE (and vice-versa).

estimation accuracy of the network and its power consumption are traded off against each other.

Using all nodes in the network offers the highest quality estimates but at the cost of the highest power consumption. The plot in figure 6.5 (right) shows trade off obtained by the algorithms developed in [26] and [27] where the estimation accuracy is measured by the mean squared error (MSE). If a modest increase in the level of the MSE is allowed, significant energy savings can be made. Alternatively, without an energy model or in the case of homogeneous sensor nodes, the network can be scheduled over a fixed number of time instances such that all nodes are activated approximately the same number of times, thus balancing the utilisation of the network. In this fashion no nodes are activated excessively while others are never used. This work has been extended to a network composed of 100 sensors [28].

6.2.4 Communications electronic warfare and electronic surveillance

The increasing sophistication of cellular technologies culminating in the release of fifth generation (5G) technologies will result in a number of challenges to communications electronic warfare (CEW) and electronic surveillance in the coming years. An example of one of these challenges is where the increasingly contested and congested electromagnetic environment will negatively affect new MIMO communication techniques. As part of the solution to mitigate these issues it will become standard to ‘get among’ the signals (i.e. sensing will no longer be carried out at a stand-off distance). To do this the sensors will need to be deployed nearer, or among, target emitters. Distributed sensor networks will therefore be standard.

A mobile ad hoc sensor network (MASNET) is a number of sensors networked together and used collaboratively to detect and process radio signals. This could comprise multiple units of the same type or combinations of sensors with different processing capabilities. An example MASNET for wireless communications signals is shown in figure 6.6. MASNETs have the advantage over static sensor networks that they can be deployed in various scenarios and cope with changing conditions. MASNETs also have applications in electronic surveillance.

In the operating environment, there are different information flows: sensor-to-sensor communications (i.e. information being exchanged between different sensors in the MASNET), target-to-target communications (i.e. the target network communicating with other nodes in the same network), and ambient sensing of radio transmissions by the MASNET sensors. Moreover, there are a number of parameters that influence the performance and capabilities of the MASNET:

- the number of sensors and targets and distance between them,
- the type of radio environment in which the MASNET is

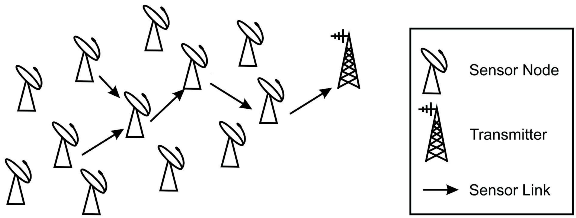

Figure 6.6: An example MASNET comprising sensors and transmitters. Sensors are not necessarily connected directly to transmitters. An example of a potential information flow is shown by the arrows.

operating,

- the type of wireless transmissions being used by the targets,
- sensor management strategies that can affect the detection, localisation and decoding of the transmissions.

Optimum and collaborative signal processing techniques are crucial to the operation of all distributed sensor networks. Such networks need to detect, position fix and decode signals collaboratively. UDRC researchers assessed MASNET performance for various scenarios. The results are reported in [29] for an urban environment where sensors and the target are geographically interspersed. They showed that detection and localisation confidence increases with number of sensors. This is expected as larger numbers of sensors increase the chances of having a sensor with sufficient received signal power to be able to detect a target. Likewise, the higher the power transmitted by the target the fewer sensors are needed to detect it because the likelihood of a sensor receiving enough power to detect is increased. Simulations were carried out using the WINNER2 channel framework [30] which allowed realistic estimation of performance.

This work helped to bound the achievable performance of real MASNET configurations that are used for sensing in wireless communication environments. The analysis made use of both stochastic propagation models and realistic ray-tracing characterisations of EM environments. This provides MOD with estimates of the number of sensors required to achieve performance targets in wireless communications and sensing applications.

MASNET enabling contract

The question of how many sensors are needed for accurate sensing of a signal in the electromagnetic environment was further addressed by the UDRC in a MASNET enabling contract designed to exploit the UDRC's fundamental signal processing results. Work carried out in the enabling contract influenced a series of field trials carried out by Dstl's CEW project, beginning in early 2018.

The aim of the enabling contract was to characterise the use of a MASNET in two generic but bounded scenarios: rural and urban. The focus was on understanding how a MASNET can pick-up emissions passively from a network of adversary radios, rather than on the network connections between the MASNET sensors themselves. An appreciation of how raw data can be combined together from the sensors was necessary. In general this needs to be undertaken in a way such that signal detection, position fixing and demodulation can be done jointly – i.e. at the data level, rather than the decision level. The project comprised three stages.

1. *Mathematical modelling* A series of mathematical models helped to answer some of the questions above. The rural and urban models used were statistical in nature and assumed typical fading parameters. At this stage

there was no need to understand specific rural or urban geometries, e.g. where buildings are located.

2. *Simulation and statistical analysis* The work from the previous stage was verified using RF simulations (for example, using ray tracing or finite element modelling). Commercial simulation software or previously developed software was used (so that the UDRC researchers could focus on the issues highlighted above and not on software creation). Unlike the previous stage, in these simulations, specific geometries were assumed and used.

3. *Real-world verification and robustness testing* Real-world RF recordings were taken to verify the simulations from the previous stage. This included, for example, a series of impulse response measurements taken from typical UK urban and rural environments. Co-channel interference was not recorded live. Impulse response measurements were taken using a channel sounder and receiver combination. These measurements were then used to pseudo-model (a combination of real world impulse responses and modelling software) different scenarios and add in co-channel or noise in post-processing.

The results demonstrated that the proposed Euclidean Distance Matrix approach could outperform the widely used Least Squares algorithm, especially when a small number of sensors were used in multipath scenarios [29].

6.2.5 Power reduction techniques for FPGA resource management

FPGAs require careful power management, and to contribute to this endeavour the UDRC has developed the concept of prior knowledge guided approximation. This is based on a statistical model of the impact of approximations[3] on power consumption, which contrasts with empirical methods that currently prevail in FPGA engineering. UDRC researchers used Kullback-Leibler (KL) divergence-based metrics[4] to evaluate approximation errors and assess whether these are within acceptable variance bounds [31]. The model uses prior knowledge to ensure sufficient accuracy where access to ground truth is impossible by dynamically modifying the level of approximation.

To optimise data requirements within FPGA implementations, UDRC researchers have developed methods for the allocation of on-chip memory to minimise resource usage and power consumption. They have contributed to the realisation of power-efficient sensor systems fully contained on FPGAs. These methods generate on-chip memory architectures which reduce FPGA memory resource usage and power consumption by approximately 35% for video processing and tracking applications [32]. They have combined sensing algorithm implementation with platform integration, algorithm hardware and software integration with sensors and network connectivity [33].

This work is unique in that it implements a supervisor block which is able to make trade-offs between accuracy and power consumption and, crucially, do this at run-time with no knowledge of the ground truth. This could have significant impact upon power usage in a scenario with deployed military sensors that must conserve processing power. Additionally, the general principles established here could easily be used in other accuracy trade-offs; most notably the accuracy against time trade-off which is always critical for ISR applications. In this scenario the intelligent algorithm would recognise situations where the

[3]As examples the researchers implemented bit width reduction (floating point to fixed point), and look up tables of basic mathematical functions (sine, cosine, arctangent, square root). However, this general principle could be extended to more sophisticated approximations such as truncation of the order of polynomials or limits on Taylor expansions.

[4]The Kullback-Leibler divergence is a distance-like metric which enumerates the difference between a pair of probability distributions.

need for a fast approximate answer is greater than the need for a highly accurate answer that is too late to be actionable, and therefore adjust the signal processing accordingly.

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Chapter 7

Highlights and future

This chapter draws out some of the overarching highlights of the UDRC phase 2. It examines outcomes, looks at next steps, and – in anticipation of UDRC phase 3 – makes recommendations for the future.

7.1 Consortium activities

The consortiums originally comprised six universities, Edinburgh and Heriot-Watt in one and Loughborough, Surrey, Strathclyde and Cardiff in the other. In 2015 Professor Jonathon Chambers, LSSC consortium lead, took up the position of Head of the Communications, Sensors, Signal and Information Processing (ComS2IP) Group at the School of Electrical and Electronic Engineering at Newcastle University. The EPSRC grant moved with him and the work on network anomaly detection (§5.1) went to Newcastle. The LSSC became the LSSCN consortium. In 2016 Neil Robertson secured a professorship at Queen's University Belfast, bringing them into the ERP consortium.

Both consortiums sought industry advice from defence primes, QinetiQ, Leonardo (formerly Selex ES) and Thales. In addition, the ERP Strategic Advisory Group (SAG) included representation from BAE Systems and SeeByte. LSSCN's Consortium Steering Group (CSG) included Texas Instruments, Prismtech and Steepest Ascent. The latter was acquired in 2013 by The Mathworks who assumed their position on the CSG. In April 2014 Atlas Elektronik joined the LSSCN. Chemring Technology Solutions (formerly Roke Manor Research and later Roke again) joined the ERP SAG in May 2014. Kaon, a systems development and consultancy company, joined the LSSCN CSG in November 2016. The list of industry partners at the close of the UDRC phase 2 is given in table 1.1.

During the course of UDRC phase 2 Professor Mike Davies of Edinburgh, ERP consortium director, and Professor Wen-Hua Chen of Loughborough were elected Fellows of the IEEE. Prof. Davies was additionally elevated to Fellow of the Royal Academy of Engineering, Fellow of the European Signal Processing Society, and Fellow of the Royal Society of Edinburgh.

Prof. Chambers was invited by the IEEE in 2015 to serve on the committee which selects the recipient to receive the Jack S. Kilby signal processing medal.[1] This is the highest honour bestowed in the field by the IEEE and the committee includes 10 world-leading practitioners.

Professor Josef Kittler, Distinguished Professor and founder of the University of Surrey's Centre for Vision, Speech and Signal Processing (CVSSP), was awarded the Chinese Government Friendship Award in 2016 for his contribution to the development of research programmes in pattern recognition and artificial intelligence at Jiangnan University. It is the highest award made to foreign experts in China.

Yan Pailhas of Heriot-Watt University (HWU) won the 2016 A. B. Wood award for young researcher of the year in the field of sonar. The A. B. Wood medal and attendant prize is awarded in alternate years to acoustics researchers based in Europe (even years) and in the USA and Canada (odd years).

[1] Jack S Kilby remains the only signal processing scientist to have been awarded a Nobel prize.

It is aimed at younger researchers whose work is associated with the sea.[2] Yan presented the medal lecture at the Acoustic and Environmental Variability, Fluctuations and Coherence conference in December 2016 at the Moller Centre in Cambridge.

A UDRC team based at Strathclyde University won the UK and overall European award at the 2016 European Satellite Navigation Competition for *GUAPO* (project title: Passive bistatic detection/classification of UAVs using GNSS satellites as sources) [1]. The innovation was the development of a passive bistatic radar system which was used to detect UAVs, with the aim of monitoring sensitive areas such as restricted airspace.

The team secured an EPSRC Impact Accelerator Account in collaboration with the Satellite Applications Catapult[3] from January to March 2017, and will further benefit from Strathclyde University funding to develop the idea further. They will then apply for Defence Accelerator funding or for an Innovate UK Emerging Technology project.

In 2016 Carmine Clemente secured a Chancellor's Fellowship in Sensors Systems and Asset Management at the University of Strathclyde and was appointed lecturer in the Department of Engineering. Carmine started his signal processing career as a PhD student in the UDRC during phase 1. His elevation from student to staff has been completed under the auspices of the UDRC and can be regarded as a very visible effect of that commitment to build a UK-based signal processing skills base. Also in 2016, Mehrdad Yaghoobi, RA on the ERP was promoted to lecturer at Edinburgh. This followed his role in the successful commercialisation of sparsity-based signal sep-

[2] Albert Beaumont Wood became one of the first two research scientists at the Admiralty to work on anti-submarine defence. He designed the first directional hydrophone and made many contributions to the science of underwater acoustics.

[3] The Satellite Applications Catapult, established in May 2013 by Innovate UK, is a company created to foster growth across the economy through the exploitation of space.

aration algorithms for Raman spectroscopy with Metrohm Raman (see §2.1.4), as well as imaging SAR work with Leonardo. Daniel Clark of Heriot-Watt secured a Royal Academy of Engineering industrial fellowship for a three-month secondment to Dstl from April to July 2017. There he provided expertise and consulted on tracking and sensor management for applications in space situation awareness, maritime sensor fusion and imagery intelligence (see §4.2.5).

Domenico Gaglione and Christos Ilioudis, then PhD students at Strathclyde University, were awarded first and third place respectively at the best student paper competition at the IEEE International Radar Conference 2015 in Washington. This is one of the most prestigious prizes that early stage researchers can win at one of the most important international radar conferences. Domenico's contribution was entitled *Model-based sparse recovery method for automatic classification of helicopters* [2] while Christos presented the paper *Performance analysis of fractional waveform libraries in MIMO radar scenario* [3].

Puneet Chhabra from Heriot-Watt was chosen as a finalist for the UK ICT Pioneers in 2015. This is a unique partnership between EPSRC and their key stakeholders, which recognises the most exceptional UK doctoral students in ICT-related topics who can demonstrate the commercial potential and impact of their research to business. The competition is open to all UK students in the final two years of their doctoral training, culminating in a showcase and award ceremony in London. Industry judges and sponsors of the competition were from EPSRC, Dstl, Hewlett Packard Enterprise, Facebook, BCS (The Chartered Institute for IT), Samsung and BT [4].

7.1.1 Related research funding

Both consortiums have successfully attracted investment as a result of their UDRC output. This amounts to extra signal processing research funding and infrastructure attributable to

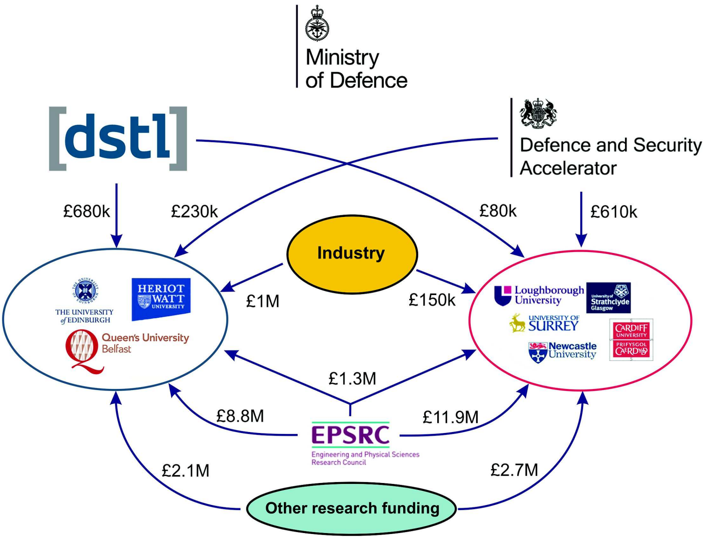

Figure 7.1: Inflow of funding from various sources to UDRC phase 2 consortiums as a result of UDRC research.

UDRC research, to the benefit of MOD and wider UK industry. For both consortiums, awards from grants, industry contracts and MOD-directed funding amount to around £30M. These funds cover more than 70 individual projects from sources including the British Council, EPSRC, the EU, MOD, US/UK multidisciplinary university research initiatives, the UK Space Agency, as well as coming from across various industry sectors including defence, automotive, entertainment and autonomy. See figure 7.1 for a pictorial representation.

7.1.2 Publicity

UDRC phase 2 has featured in the Financial Times [5], Herald newspaper [6] and Forbes [7] outlining the impact of the UDRC research. In each, Professor Mike Davies, ERP consortium lead, gave an insight into the importance of developing new software to process information acquired from the range of sensors present in the modern battlefield, from traditional radar and sonar, to ubiquitous mobile phones.

In May 2015, the UDRC featured in the MOD Defence Contracts Bulletin (DCB) [8]. The DCB is published in association with Defence Equipment and Support (DE&S) and the Defence Infrastructure Organisation (DIO) - key agencies of MOD procurement. DCB is aimed at organisations that engage with MOD as suppliers, as well as by MOD's own buying community. The article was written to inform customers in procurement of the benefits of the UDRC's collaborative approach, and promoted the approach as an example of best practice in MOD-directed low-TRL research. It also highlighted several specific examples of research pull-through that are already being exploited by government and industry.

Aspects of UDRC research have been reported on the BBC [9], in Professional Security Magazine [10], The Daily Record [11], Process Engineering [12], Technology Networks [13], The Scotsman [14], Laboratory Talk [15], Eureka! [16], Edinburgh News [17], Chemicals Technology [18], Gradcracker [19], Holyrood [20] and FutureScot [21].

7.2 Facilitating industrial exploitation

The UDRC has spawned a number of collaborative opportunities with industrial partners, ranging from joint proposals for MOD funding, to industrial studentships, secondments, and licensing agreements for the use of UDRC algorithms. These interactions are crucial to ensure that UDRC research is commercialised and made available to wider UK industry as well as MOD.

7.2.1 Intellectual property and licensing arrangements

In accordance with the Government's aims for exploitation of the output of research work funded by the Research Councils, the institutions within the consortiums are expected to claim title to the intellectual property resulting from their work and exploit the results. The MOD has standard industry-approved rights to use the results of the research. UDRC phase 2 researchers have filed for patent protection to cover two inventions.

- A method of analysing radio frequency signals using sub-Nyquist sampling, (Edinburgh), filed 31st May 2014 [22].
- Aerial object monitoring system, (Strathclyde) UK patent application number GB1718885.5 [23].

Edinburgh University have licensed the UDRC-developed algorithm for separating components of spectral mixtures to Metrohm Inc. Metrohm's latest generation of Raman spectrometers incorporate this algorithm. See section 2.1.4 for more detail.

The ERP consortium secured a contract for consultancy and licensing of SAR imaging software to SEA Ltd. The software was licensed to SEA for 2014 and 2015. The consultancy involved the delivery of a white paper on the potential for compressive sensing to be used in 3D low-frequency SAR.

7.2.2 Sensor Signal Processing and Security Laboratory, Strathclyde University

In part due to the continuity of phase 1 and 2 UDRC research, and with EPSRC funding, the Sensor Signal Processing and Security Labs opened in Strathclyde in 2015. This establishment fosters a collaborative radar research environment and hosts international visitors. In 2015 Professor Chris Baker from

Ohio State University (OSU) and Professor Antonio di Maio of the University of Naples visited. Industry partners include Leonardo (formerly Selex-ES), QinetiQ, Thales, BAE Systems, Texas Instruments, National Instruments, and Tannoy. Under a reciprocal arrangement the Strathclyde RA, Carmine Clemente, spent 3 weeks at OSU, in 2015 and two PhD students, Christos Ilioudis and Domenico Gaglione, were invited to present their work at the nearby US Air Force Research Laboratory.

7.2.3 Robotarium

Robotarium is a joint venture between Edinburgh and Heriot-Watt supported by EPSRC and industry centred on a capital equipment investment of £7.2M. The vision is for a national UK facility for research into the interactions between robots, environments, people and autonomous systems. It harnesses the expertise of over 30 principal investigators of international standing from 12 cross-disciplinary research groups and institutes from the School of Engineering and Physical Sciences and the Department of Computer Science at Heriot-Watt University, and the Schools of Informatics and Engineering at the University of Edinburgh.

The facility includes an EPSRC Centre for Doctoral Training in robotics and autonomous systems which trains innovation-ready postgraduates. The strategic aim of the Centre is to supply the urgent need for skilled, industry and market aware researchers in robotics and autonomous systems. Centre partners include global companies in the oil and gas, assisted living, transport, defence, medical and space sectors.

7.2.4 Industry events

The *UDRC Industry Day* was held at Heriot-Watt University on the 27th June 2014 with the aim of raising awareness of the work done in UDRC and its exploitation potential to industry. Case studies of UDRC-industrial collaboration and potential funding mechanisms that can support further exploitation were explored. The day was structured around interactive sessions from UDRC and case studies from industry contributors. Subjects included networked MCM using collaborative unmanned systems (SeeByte and Heriot-Watt University), Faster SAR-MTI (Selex ES and Edinburgh). Collaborations between Strathclyde and Selex ES and Strathclyde and Mathworks were also explored. There were also presentations by the CDE, the Technology Strategy Board (the predecessor of Innovate UK[4]) and the Knowledge Transfer Network in Electronics, Sensors and Photonics.[5]

In each of 2014, 2015 and 2016 the LSSCN CSG meetings were preceded by an industrial show-and-tell afternoon. The aim of these events was to see state-of-the-art signal processing solutions on real-time devices in an industrial setting. They also facilitated UDRC-industrial contacts and started the process of identifying new avenues for exploitation of UDRC research. Talks, posters and demonstrations covered, amongst other things, embedded multi-core systems for image processing and tracking, system design and implementations in SDR, micro-Doppler classification, methods of tracking and identifying space debris, and communicating radar. Contributions came from The Mathworks, Texas Instruments, National Instruments and Lockheed Martin as well as the UDRC universities. A phased-array toolbox available from Mathworks which is based, in part, on work done during the phase 1 of the UDRC was demonstrated in 2015.

In both 2015 and 2016 Edinburgh University hosted an *AIMday.* The AIMday concept is a series of single-day meet-

[4]Innovate UK is a public body reporting to the Department for Business Energy and Industrial Strategy, which seeks to promote growth in the UK economy by supporting business-led innovation.

[5]The Knowledge Transfer Networks are an Innovate UK initiative which look to build links between established businesses and markets and the latest discoveries and new ideas, to benefit the UK economy.

ings focussed on making contacts between companies or organisations and academic researchers from specific sectors (in the UDRC case, sensor systems and signal processing). The meetings' stated intent are to match industry challenges with academic expertise. Industry questions are submitted in advance and used as a starting point for discussion.

The 2016 AIMday was opened by Dstl, who summarised the achievements of the UDRC. Members of the UDRC leadership team were present in most of the industry-led workshops. The event was judged by the Dstl attendees to be a useful engagement mechanism with industry, using a novel format to catalyse discussions at a technical level about industrial problems.

7.2.5 The polynomial-matrix eigenvalue decomposition toolbox for Matlab

With LSSCN addressing efficient implementations, the CSG recommended the realisation of one algorithm as a sample implementation in software. An iterative algorithm for polynomial matrix eigenvalue decomposition (PEVD) was chosen, as this was of importance to several activities across the consortium, in particular broadband source separation and subspace techniques (see §2.2.2 and §6.1). This has been packaged up as a toolbox for use with Matlab and has been promoted with the help of LSSCN's industrial partner The Mathworks for use by the wider Matlab community. The toolbox is available at [24]. To date there have been over 100 downloads. The authors (Dr Stephan Weiss and Prof. John McWhirter, supported by Jamie Corr and Zeliang Wang) delivered a tutorial based on the toolbox at the IEEE Sensor Array and Multichannel Signal Processing workshop held in Brazil on 10th-13th July 2016. The PEVD toolbox was also showcased at the first international workshop on polynomial matrix decompositions and their applications (§7.4.7).

7.2.6 PhD CASE studentships and EngD studentships

During the course of UDRC phase 2 the ERP consortium secured 8 EPSRC Collaborative Awards in Science and Engineering (CASE) or Engineering Doctorate (EngD) studentships. These are not funded by the UDRC but address UDRC problems. The studentships have a significant industrial focus, with the business partner taking the lead in directing the student's research. The projects are:

- "Target detection and classification from an airborne mobile platform" with Leonardo (formerly Selex ES) at Edinburgh University
- "Adaptive waveform design in a crowded spectrum" with Leonardo at Edinburgh
- "Contextual anomaly detection" with Roke at HWU
- "Multiple vehicle collaboration" with Seebyte at HWU, started in September 2016
- "Fast Lidar imaging systems for cars" with ST Microelectronics at HWU and Edinburgh, started in September 2016
- "Real-time implementations of tracking algorithms and estimation of algorithms for radar systems" with Leonardo at Edinburgh, started in September 2016
- "Non-linearity in the RF sensing chain" with Leonardo, started in September 2017
- "Wireless channel models for Fifth Generation wireless systems" with The Mathworks

7.3 Advice and consultancy

UDRC academics have provided signal processing expertise to people and projects in MOD, wider Government and industry. These have ranged from exploratory workshops covering a broad range of topics to more focussed and in-depth efforts which look at a particular defence need. In many cases the latter formed the basis for follow-on contracts using enabling agreements or industry funding. During phase 2 UDRC academics consulted on a number of MOD problems including array signal processing, novel tracking algorithms, temporal anomaly detection and intelligence fusion.

7.3.1 Missile Defence Centre

In 2014 the LSSCN consortium was approached by the Missile Defence Centre (MDC) to consider potential novel techniques to mitigate the threat posed from ballistic missiles. The consortium put forward an integrated surveillance system concept that offered early detection and tracking of missiles, and novel target characterisation techniques for kill assessment.

The concept is underpinned by the spectrum of potential ballistic missile threats: short, medium and intermediate-range missiles; single or multiple missile attacks; and static or mobile launch sites. UDRC researchers proposed a networked multimodal sensor environment to provide the maximum information in order to make informed real-time kill assessment. The concept is based around local and central fusion of information from widely distributed networked sensors, including low earth-orbit satellites, early warning radars, and other legacy systems. In addition the UDRC team proposed the concept of augmenting these systems with relatively low cost multi-static radars and MIMO radar technology. A key part of the concept was the use of micro-Doppler analysis to identify targets from clutter.

Strathclyde University secured a contract through a CDE themed call to adapt radar micro-Doppler techniques developed during UDRC phase 2 to the problem of target classification for ballistic missile defence. The project demonstrated the ability to provide reliable discrimination of warheads from other objects such as debris and spent stages, accurate orientation of the warhead at the predicted instant of impact, and a determination via changes in signature for kill-assessment purposes.

Other work has been carried out at Heriot-Watt University on space situation awareness under an enabling contract (see §4.2.3). Applied research related to ballistic missile tracking has taken place at Loughborough University (see §4.1). The next steps for MDC-sponsored research consider the following topics.

- *Joint radar waveform and filter bank design for ballistic targets classification* This activity will investigate the potential capabilities of a joint transmitting radar waveform design and receiver filter bank for the specific purpose of ballistic missile classification. Both the micro-Doppler and high resolution range profile radar modes will be considered in the analysis.

- *Missile launch detection from small satellites* This activity looks at assessing the detection of thermal anomalies (fires) from near- and medium-IR images collected on board small satellites, in order to detect potential missile launches. Using a small platform (e.g. a CubeSat) provides advantages in terms of cost and potential number of sensors available. It introduces, however, constraints in terms of the sensor capabilities. It is likely that only a low spatial resolution imager would be available onboard, thus there is a need to develop reliable detection algorithms able to detect thermal anomalies on a subpixel scale. Constant false alarm ratio detectors, known for their reliability and low computational cost will be developed in this task, together with a system functional design.

7.3.2 Warfare in the information age

Warfare in the information age (WitIA) is the title of a letter written by General Sir Richard Barrons, Commander Joint Forces Command (JFC) in 2014. The letter outlined his thinking on how the information age is changing warfare, emphasised the extent to which some of the UK adversaries were exploiting the potential of information to deliver military operations in new, more effective ways, and made the case for change to ensure that UK Armed Forces were both able to exploit the opportunities and counter the threats presented by the information age.

Following General Barrons' letter, Dstl were tasked to conduct a study in order to help JFC deepen their understanding of how the information age has changed warfare, generate options to respond and to develop a plan to enable JFC to 'operationalise' the vision outlined in WitIA. As part of that effort Dstl organised a WitIA conference at Porton Down in 2016. The brief was to showcase technologies which have significant potential to make an impact on information-age warfare. At this event the UDRC presented selected highlights from their work on compressive sensing and sparsity, anomaly detection in networks and WAMI, tracking and sensor management, as well as efficient implementation.

7.3.3 Network and Information Sciences International Technology Alliance

The UK/US International Technology Alliance in Network and Information Sciences (NIS-ITA) was formed in May 2006 to undertake fundamental (TRL 1-2) research in network and information sciences. Following a successful first 5-year phase, the NIS-ITA program was extended to 10 years in May 2011 with a research programme focussed on network sciences. The NIS-ITA is a joint MOD/Dstl and US Army Research Laboratory programme, involving an IBM-led consortium of twenty four industry and academic organisations from the two countries. The NIS-ITA concluded in 2015 and its mantle has been assumed by the US/UK DAIS ITA project [25].

In 2014 the UDRC and NIS-ITA held a joint meeting. Over 40 experts attended from across the two communities with the aim of exploring topics of common interest and identifying specific actions to enable joint working. As a result of this meeting, several opportunities for collaboration were identified. These included using UDRC algorithms on the NIS-ITA experimental network, studying how algorithm performance degrades with decreasing network connectivity, mapping algorithms to distributed architectures, exploring local distributed and central processing, and doing distributed anomaly detection.

7.3.4 CCS innovation day

The Technology Concepts strand of Dstl's C4ISR Concepts and Solutions (CCS) project held an academic workshop in December 2014. A number of UDRC academics took part. The workshop drew from the CCS "Engine Room" community as well as from UDRC. The first session of the workshop introduced eight military topics. These were derived from an endorsed list of capability gaps, issues and systems concepts which were areas of interest to the CCS project. The attendees selected three topics for further exploration in the workshop.

1. *Networking for multiple platforms and sensors to enable maritime situational awareness and understanding* Future maritime operating environments will see a proliferation of unmanned vehicles and associated sensors. This is both an opportunity and a risk for maritime situational awareness and understanding.

2. *Multi-dimensional persistent wide-area surveillance* It is challenging to maintain PWAS in an operational theatre across 'all-frequencies and all sources', fuse relevant information and present it in a defined, consistent format.

The absence of such processing results in a reduction in the operational effectiveness of deployed formations, and a increase in the operational risk.

3. *Low-cost ISR to mitigate the more contested and cluttered airspace of the future* The issue is how to make use of a greater number of low cost and reduced capability ISR air platforms. The future battlespace will be more cluttered and constrained. In the air, the ability to operate will be contested. High capability ISR assets are likely to be high value targets.

Each of the topics was discussed in syndicate and plenary sessions, looking at barriers and enablers, systems issues and timescales. The results of these discussions were used to inform the next round of concept planning for the CCS project in 2015 and eventually the Dstl response to the WitIA memo (see §7.3.2).

7.3.5 Astrodynamics Community of Interest

In 2016 Dstl presented the UDRC concept and relevant UDRC work at the Astrodynamics Community of Interest (ACI) workshop at the University of Warwick. The ACI comprises universities, industry, the UK Space Agency and Dstl. ACI members subsequently participated in the UDRC themed meeting on space and tracking in November 2016. Throughout the course of UDRC phase 2 Dstl and the ACI supported the SSA work led by Heriot-Watt University by providing funding, advice and exploitation routes.

7.4 Development of signal processing science

This section provides a brief summary of some academic highlights emerging from the UDRC. A full list of journal papers and conference proceedings is available at mod-udrc.org.

During the course of the phase 2, UDRC researchers have produced over 300 publications. Dstl vetted each one to ensure that no sensitive information was disclosed. Approximately two thirds of submissions have been in conference proceedings and the rest in peer-reviewed academic journals. All conferences have been IEEE indexed, which means they are high calibre with competitive submissions and robust review. All journals are internationally renowned with expert reviewers. There have also been examples of significant contributions to signal processing science undertaken by the UDRC consortiums working together. The most obvious of these were the annual SSPD conferences and the UDRC summer schools, though other examples include SPAWC 2016 (§7.4.5), and the Universities of Newcastle and Heriot-Watt jointly securing a £1.3M EPSRC grant. This latter project, entitled *USMART - smart dust for large scale underwater wireless sensing* is a 3 year collaboration also including the University of York to develop affordable technology for large scale, smart wireless sensing networks to be deployed in the oceans.

7.4.1 Signal Processing for Defence at ISCCSP

The LSSCN consortium organised a special session entitled "Sensor Signal Processing for Defense" at the 6th International Symposium on Communications Control and Signal Processing (ISCCSP), sponsored by the IEEE Signal Processing Society, in Athens in May 2014. The symposium was attended by approximately 150 delegates and the structure of the special session, chaired by Prof. Jonathon Chambers (LSSCN consortium lead), was:

- Analysis dictionary learning based on Nesterov's gradient with application to SAR image despeckling; Jing Dong, Wenwu Wang (University of Surrey)

- Reuse of fractional waveform libraries for MIMO radar and electronic countermeasures; Carmine Clemente, Christos Ilioudis, Domenico Gaglione, Keith Thompson, Stephan Weiss (University of Strathclyde), Ian Proudler (Loughborough University), John J Soraghan (University of Strathclyde)
- Game theoretic power allocation technique for a MIMO radar network; Anastasia Panoui, Sangarapillai Lambotharan, Jonathon Chambers (Loughborough University)
- Estimating adaptive coefficients of evolving GMMs for online video segmentation; Ioannis Kaloskampis, Yulia Hicks (Cardiff University)

This successful activity highlighted the work of the UDRC internationally and increased interest and attendance at subsequent SSPD events.

7.4.2 International Conference on Pattern Recognition Applications and Methods, 2014

Professor Josef Kittler (LSSCN, Surrey) delivered an invited keynote at this conference held on March 6-8 2014 in Angers, France. The conference was on ”Applications of pattern recognition techniques to real-world problems”. Prof. Kittler’s keynote covered his UDRC work on anomaly detection methods and classifier incongruence determination.

7.4.3 Electronic Warfare Symposium

Prof. Chambers was invited to deliver the keynote address at the 2015 Electronic Warfare Symposium at the Defence Academy of the United Kingdom at Shrivenham. The talk was entitled “The University Defence Research Collaboration (UDRC): an agent for change in ES”. The presentation was well received, and UDRC researchers were subsequently invited to participate in a classified RF EW technical conference at Cranfield University.

7.4.4 International workshop on compressed sensing theory

Professor Mike Davies, ERP consortium lead, was invited to give a keynote talk at the international workshop on compressed sensing theory and its applications to radar, sonar and remote sensing (CoSeRa 2016) in Aachen, Germany in 2016. Prof. Davies spoke on the UDRC work on compressive sensing for SAR imaging. The title was “Sparse signal separation and imaging in synthetic aperture radar”. This meeting also included Dstl radar representation.

7.4.5 International workshop on signal processing advances in wireless communications

UDRC academics were successful in bringing the The 17th IEEE international workshop on signal processing advances in wireless communications (SPAWC 2016) conference to Edinburgh in 2016. This conference brought together researchers, industrial and academic, to share advances in signal processing in wireless communications and wireless technology. The co-chairs were Professor Mathini Sellathurai (Heriot-Watt) and Prof. Chambers. Professor John Thompson (Edinburgh) was the tutorial session chair.

7.4.6 Mathematics in signal processing

There was significant UDRC representation at at the IMA international conference on mathematics in signal processing in Birmingham during December 2016. Prof. Chambers was the conference co-chair and Prof. Davies was invited to give the keynote talk, "Exploiting structure and sparsity in defence signal processing: from spectral decomposition to radar compressed sensing". Professor Sangarapillai Lambotharan (Loughborough) also gave an invited talk, on "Game theory and its applications in wireless communications and sensing systems."

7.4.7 Polynomial matrix workshop

The first international workshop on polynomial matrix factorisation (PMF) techniques and applications workshop was held at Chicheley Hall from the 25th to 26th August 2016. The workshop was attended by 20 participants from around the world.

Matrix diagonalisation is a common element in solutions to linear systems and becomes computationally expensive with large systems and the need for fast solutions. Finding low cost solutions has been the main driver behind the interest in PMF. The workshop introduced PMF and PEVD (c.f. §7.2.5): a specific form of PMFs. The solutions to PEVDs were discussed and the popular iterative algorithm SBR2 focussed on. An improved multiple shift sequential SBR2 (MS-SBR2) was presented; SBR2 is considered a fast way of carrying out a PEVD at a reasonable computational cost. The participants also discussed applications and various papers on this subject were presented. They included MIMO channel equalisation in communications, broadband MIMO, signal separation, blind source separation, angle of arrival estimation including broadband minimum variance distortionless response (MVDR) beamforming and broadband sonar arrays.

Narrowband solutions and applications are well established and transforming them to the broadband domain has been challenging. PEVD is an effective way to apply or solve broadband beamforming and equalisation problems. The workshop demonstrated how to transform an existing narrowband solution to an effective broadband solution. Two examples were shown, including a narrowband sidelobe cancellation problem transformed to broadband by using the PEVD. The other showed a narrowband MVDR beamforming being transformed into a broadband MVDR application by using the PEVD.

7.4.8 Joint trials between UDRC and CMRE

In September and October 2016, UDRC researchers at Heriot-Watt participated in the ONMEX'16 and the MANEX'16 trials. These trials were organised by the NATO Centre for Maritime Research and Experimentation (CMRE), and took place respectively in the Bay of Hyeres, close to Toulon in France and in Framura in Italy. Broadband sonar data was collected with the Hydrason BioSonar ultra-wideband sonar array. This novel hardware relies in part on research outputs from the UDRC phase 2.

In total more than 20 missions were performed. An autonomous underwater vehicle traveled over 175km inspecting around 13km^2 of seafloor. The general scope of these trials was to collect a substantial data set using a wideband multibeam sonar (WBMBS) system and three sidescan sonars to study issues of coherence. The WBMBS has sensitivity over a very broad range in frequency (20 − 180kHz). It also has a very wide beam pattern (40° @ 60kHz). In a similar way to SAS systems, the WBMBS sees every point in the scene numerous times. It is therefore particularly well adapted to measure spatial coherence. The multi-element aspect of the WBMBS enables, via adaptive processing, maximisation of the signal over reverberation ratio, and thereby a cleaner measurement of the coherence of a particular point in the scene. The aim of the trial was to carry out repeated measurements at different grazing angles and aspects in a number of environments to assess the limit of coherence loss and its dependency on look-angle, frequency, seabed type. A special emphasis was placed on man-made targets present in the environment and polygonal or circular target re-acquisition was performed. The trials delivered a vital data set which addresses fundamental questions about coherence, as well as material to develop recognition algorithms based on coherence processing.

7.5 UDRC Data Centre

Dstl hosts the UDRC Data Centre, a repository of a broad range of unclassified defence-related data gathered from a variety of sensors observing many different types of target and environment. At the end of phase 2 the size of the repository was in excess of 80TB. A catalogue is available at [26].

The overarching goal of the Data Centre is to support the fourth objective of the UDRC to facilitate the rapid exploitation of signal processing science and technology to address military requirements. It also aims to provide a mechanism by which data can be shared between academic collaborators for the advancement of signal processing research. This is in line with the Prime Minister's Transparency Agenda, under which MOD has published its Open Data Strategy. MOD is committed to ensuring that the maximum value is derived from data by ensuring its re-use within the Department, across government, and wherever feasible, by the public and developer community. Dstl has sought, where possible, to make the data published by the UDRC Data Centre compliant with the standards laid down in the policy, taking into account protective marking and commercial sensitivities.

During phase 2 of the UDRC there were 63 transfers of data to academic and industry institutions, covering releases to develop algorithms, as well as more short-term technical challenges. More efficient release processes to UDRC researchers have been developed. The average time between request and data release was around 2 weeks (a similar timescale as is involved in paper clearances).

At SSPD 2015 conference Dstl presented a data challenge centred on FMV. The challenge included 370GB of data from an airborne platform and asked researchers from the whole community (not just UDRC) to demonstrate automated methods of annotating video streams. These activities are currently undertaken by intelligence analysts, but are potentially amenable to image processing, target recognition and machine learning algorithms. Challenges such as these came to be the preferred method for distribution of unclassified data in that a single process covered release to all parties, and necessary bureaucracy was minimised. It also ensured that recipients were motivated to develop solutions which address issues in the data directly, and seek early engagement with Dstl who are able to understand and affect the proposed method. A number of such releases have since been made to the UDRC project manager who manages and maintains the onward distribution list. Where possible, available data sets have been advertised on the UDRC website [26].

7.6 Summary and the next stage

This book has described the research and development conducted under phase 2 of the University Defence Research Collaboration (UDRC) in Signal Processing. UDRC phase 2 was a 5-year, £11.5M programme centred on an £8M joint venture between MOD and the Engineering and Physical Sciences Research Council (EPSRC). It began in 2013, and was entitled *Signal processing in a networked battlespace.*

The UDRC phase 2 was originally composed of six universities formed into two consortiums. This later became eight universities. During its term it has been delivered by 24 academic staff, 28 Research Associates, over 20 PhD students and 4 project management staff, as well as a number of Dstl technical experts and project managers. Jointly, the consortiums' programmes of work were made up of many individual projects covering all aspects of signal processing research. Each project addressed a number of technical challenges in defence-oriented signal processing.

The UDRC will continue to provide MOD with direct access to a talent pool that is deployable on MOD problems at short notice. During phase 2 experts were consulted in depth on a wide range of defence signal processing challenges. Particular breakthroughs were made in the topics of array processing, novel tracking, anomaly detection and intelligence fusion.

A total of 12 enabling agreements were let with Dstl, representing over £750k worth of funding to further develop UDRC innovations for UK military use. The core UDRC phase 2 grant has been instrumental in securing a further £30M from other government and industry sources, advancing and exploiting signal processing R&D in both the defence and civil sectors.

Exploitation of phase 2 technology will continue and various mechanisms exist to do this. The most direct approach is to allocate MOD funding to further develop phase 2 technologies. More complex and innovative options are available. Dstl and Innovate UK have discussed using Knowledge Transfer Partnerships (KTPs) to facilitate exploitation from academia to industry. In mechanisms like this an industrial partner recruits an employee to work on bringing in a new technology from an academic partner, the knowledge residing in the new recruit. An academic panel oversees the transfer. Government provide some degree of matched funds toward the total project costs. More broadly, schemes exist which cover transfers of algorithms, recruitment of individuals, as well as other means of nurturing technical staff in an industrial setting. Whatever the mechanism for exploitation, it's clear that Dstl will continue to be engaged in assessing the totality of the work under phase 2 to provide recommendations for work to carry forward.

The UDRC phase 2 has been highly successful, delivering an integrated programme of research, with engagement from strategic industrial partners who provided commercial driving force, and have brought research outputs closer to exploitation. A number of instances of UDRC research have already been applied directly to MOD signal processing problems to the benefit of the UK and its international partners. There have been over 300 publications in phase 2, some in the most significant peer reviewed journals such as IEEE Transactions. Examples of breakthroughs are found in fields such as low-frequency synthetic aperture radar imaging, micro-Doppler technologies for target detection and multi-target tracking algorithms.

Toward the end of 2015, Dstl and EPSRC entered into dialogue regarding a successor programme to the UDRC phase 2. In no small part due to the successes of the past five years, EPSRC and Dstl agreed to continue UDRC with a phase 3 programme under the title *Signal processing in the information age*. Both parties, moreover, have a strong desire to see the current research continue to be exploited beyond the end of the present funding term, to derive ongoing benefit from the world-leading signal processing research undertaken during this phase.

As MOD and EPSRC look to the future, they should seek to build on the vibrant collective built by UDRC phase 2, the goal being to sustain and fortify the UK's hard-won defence signal processing talent. It is recommended that future research programmes should follow the lead of the UDRC and promote deep technical expertise, facilitate knowledge exchange between researchers and practitioners and encourage greater participation in a growing community of practice. These factors will serve to further strengthen the UK defence signal processing community which has benefited greatly from the phase 2 of the UDRC.

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Glossary

ADC	Analogue-to-Digital Converter
AFRL	US Air Force Research Laboratory
AIS	Automatic Identification System: a system used in maritime situation awareness in which vessels report information regarding their state at periodic intervals, or in response to queries from a transmitter. The reporting period varies according to location. AIS is mandatory (under the International Maritime Organization's International Convention for the Safety of Life at Sea) for all vessels with over 300 gross tonnage. It is employed by many others besides.
APT	Advanced Persistent Threat: a category of cyber attacker
ASW	Anti-Submarine Warfare
ATR	Automatic Target Recognition
AUV	Autonomous Underwater Vehicle
AV	Autonomous Vehicle
Broadband	Indicating a signal whose power is distributed over a wide range in frequency
Capon beamformer	A type of MVDR beamformer; an adaptive beamformer whose goal is to minimise the received signal's variance
CB	Chemical and Biological
CBR	Chemical, Biological and Radiological
CDE	Centre for Defence Enterprise: a MOD-funded innovation scheme, superseded in 2016 by the Defence and Security Accelerator (DASA)
CEW	Communications Electronic Warfare
CMRE	NATO Centre for Maritime Research and Experimentation
CNN	Convolutional Neural Network: a deep variant of an artificial neural network. CNNs have been successfully applied to object recognition and image processing tasks in recent years.
COTS	Commercial Off-the-Shelf: indicating that the technology is available for purchase in the civil sector
CSA	MOD Chief Scientific Adviser

CubeSat	A miniature low-cost satellite equipped with a lightweight and relatively inexpensive payload. CubeSats may be launched as secondary payloads and in large numbers making them extremely good technology demonstration platforms.
DASA	Defence and Security Accelerator: a MOD-funded innovation scheme designed to steward innovations which can provide advantage to defence and national security from inception to application
DBN	Deep Belief Network: a neural network based machine learning technique that exploits deep learning methods
DDoS	Distributed Denial of Service: a type of (relatively unsophisticated) cyber attack
DEM	Digital Elevation Model
DE&S	Defence Equipment and Support: an arm's length body of MOD tasked with buying and supporting the equipment and services that the Royal Navy, British Army and Royal Air Force need to operate effectively
DOA	Direction of Arrival
DSP processor	Digital Signal Processing processor: a specialised microprocessor whose architecture is optimised to the requirements of digital signal processing
EO	Electro-Optical
ES	Electronic Surveillance
EVD	Eigenvalue Decomposition: a matrix manipulation where a matrix may be decomposed into a canonical form to reveal its dominant factors
EW	Electronic Warfare
FISST	Finite Set Statistics: an alternative approach to multi-target tracking schemes which seeks to avoid the curse of dimensionality by representing collections of objects as sets
FMV	Full Motion Video: video streams typically with small fields of view, high spatial resolution, and high frame rates. Contrast with Wide-Area Motion Imagery (WAMI).
FPGA	Field Programmable Gate Array: a programmable integrated circuit device that allows an algorithm to be implemented efficiently in hardware
FrFT	Fractional Fourier Transform: a generalisation of the Fourier transform in which signals are represented not only with respect to time or frequency, but a fractional combination of both

Gaussian Process	The basis for a machine learning method for regression and classification of signals. Gaussian Processes assume that observations are drawn from a stochastic process, a set of functions, whose random variables are multivariate Gaussian distributed.
GMTI	Ground Moving Target Indication: a type of radar sensing mode sensitive to targets moving radially with respect to the sensor. It is capable of covering very large areas for significant periods of time allowing patterns and activities to be observed.
GPS	Global Positioning System: a set of US military satellites providing signals which allow accurate self-localisation to those with receivers. More generally, any similar system of global navigation satellites, e.g. EU's Galileo, Russia's GLONASS.
GPU	Graphics Processing Unit: a processor originally designed for the swift rendering of graphics, characterised by its parallel processing capability. Many algorithms can be adapted to exploit this parallelisation to achieve huge computational savings.
HISP	Hypothesised Filter for Independent Stochastic Populations: a UDRC-developed state estimation method based on point process theory which has been applied to space situation awareness and underwater target tracking
HSI	Hyper-Spectral Imagery: a hybrid imaging and spectral sensor where each pixel in an scene delivers a spectrum. This enables spatially-diverse material identification. Compare with (in general) lower spectral resolution but higher spatial resolution of MSI.
IEEE	The Institute of Electrical and Electronics Engineers
Innovate UK	At one time known as the Technology Strategy Board, Innovate UK is a public body reporting to the Department for Business, Energy and Industrial Strategy, which seeks to promote growth in the UK economy by supporting business-led innovation.
INU	Inertial Navigation Unit
IR	Infrared
IRST	Infrared Search and Track
ISR	Intelligence, Surveillance and Reconnaissance
ISTAR	Intelligence, Surveillance, Target Acquisition and Reconnaissance
JFC	Joint Forces Command

LTE	Long-Term Evolution: a standard for high-speed wireless communication for mobile devices
MarCE	Maritime Collaborative Enterprise: a community of interest and contracting framework managed by BAE Systems which undertook research and development, on behalf of Dstl, of relevance to MOD maritime stakeholders.
MAP	Maximum A Posteriori: refers to a number of statistical methods that rely on finding the maximum point in the posterior probability distribution.
MASNET	Mobile Ad Hoc Sensor Network
MDC	Missile Defence Centre: a UK government/industry consortium undertaking R&D into aspects of ballistic missile defence.
MMSE	Minimum Mean Squared Error
MSI	Multi-Spectral Imagery: imaging in many spectral bands. This allows greater discrimination of objects than using panchromatic, or standard colour imagery. Compare with HSI where each pixel produces a full spectrum. In general MSI will have better spatial resolution but poorer spectral resolution than HSI.
MUSIC	Multiple Signal Classification: an algorithm for the estimation of DOA of multiple overlapping signals
MVDR	Minimum Variance Distortionless Response
Narrowband	In signal processing, a signal whose bandwidth occupies a small range in frequency
NATO	North Atlantic Treaty Organisation
NIDS	Network Intrusion Detection System
NIS-ITA	Network and Information Sciences International Technology Alliance: a UK/US collaboration formed in May 2006 to undertake fundamental (TRL 1-2) research in network and information sciences
Nyquist sampling	A fundamental result in signal processing stating that any bandwidth-limited signal may be completely characterised if samples are taken at a rate of twice the highest frequency component in that signal or higher. It establishes a sufficiency criterion whereby additional sampling of a signal yields no new information.
OFDM	Orthogonal Frequency Division Multiplexing: a technique to allow waveforms to share the same spectrum without interfering. A practical method that is in use in communications to allow multiple users to occupy parts of the spectrum simultaneously.

PDF	Probability Density Function: a function describing how the probability of an outcome, $P(x_1, ..., x_n)$, depends on the variables $x_1, ..., x_n$
PEVD	Polynomial Eigenvalue Decomposition: an extension of EVD methods to polynomial matrices
Polynomial matrix	An extension of a matrix in which each element is represented as a polynomial function, rather than a scalar value
PWAS	Persistent Wide-Area Surveillance
RF	Radio Frequency
SA	Situation Awareness
SAPIENT	Sensing for Asset Protection using Integrated Electronic Networked Technology: a concept for networked autonomous sensor modules that communicate low bandwidth detection and classification messages rather than raw data, being developed by Dstl under CSA funding and addressing scenarios including base protection, anti-vehicle area denial and counter-UAV
SAR	Synthetic Aperture Radar
SAS	Synthetic Aperture Sonar
SBR2	Second-order Sequential Best Rotation: a PEVD algorithm
SDR	Software Defined Radio
SINR	Signal to Interference and (or plus) Noise Ratio
SMD	Sequential Matrix Diagonalisation: an iterative PEVD algorithm developed under UDRC phase 2
SNR	Signal to Noise Ratio
SSA	Space Situation Awareness
SVM	Support Vector Machine: a machine learning approach to classification problems
SWAP	Size, Weight and Power
TBD	Track-before-detect: these algorithms dispense with a detection process and instead operate directly on sensor output. Targets at low SNR which may have escaped beneath a detection threshold can be found. TBD methods are generally more computationally expensive than methods with a detection step.
TRL	Technology Readiness Level: a measure of the maturity of a technique, method or product where high indicates something repeatedly field-proven or commercially available, and low suggests something untested or unfielded, perhaps only accessible as a benchtop demonstration or paper study

TTCP	The Technical Collaboration Program: a joint Australian, Canadian, New Zealand, USA and UK collaboration to advance defence-related research and development, and promote mutual reliance between the nations
UAS	Unmanned Air System
UAV	Unmanned Aerial Vehicle
WAMI	Wide Area Motion Imagery: video, often rendered at low frame rates, but covering very large areas with very high pixel counts enabling behaviours to be observed across complex scenes. Contrast this with FMV.
WiMAX	Worldwide Interoperability for Microwave Access: a family of wireless communication standards
WitIA	Warfare in the Information Age: the title of a letter written by General Sir Richard Barrons, Commander Joint Forces Command (JFC) in 2014 outlining his thinking on how the so-called information age is changing warfare
Zero-day attack	A type of cyber attack characterised by its appearance in the wild prior to the vulnerability on which it is based becoming generally known

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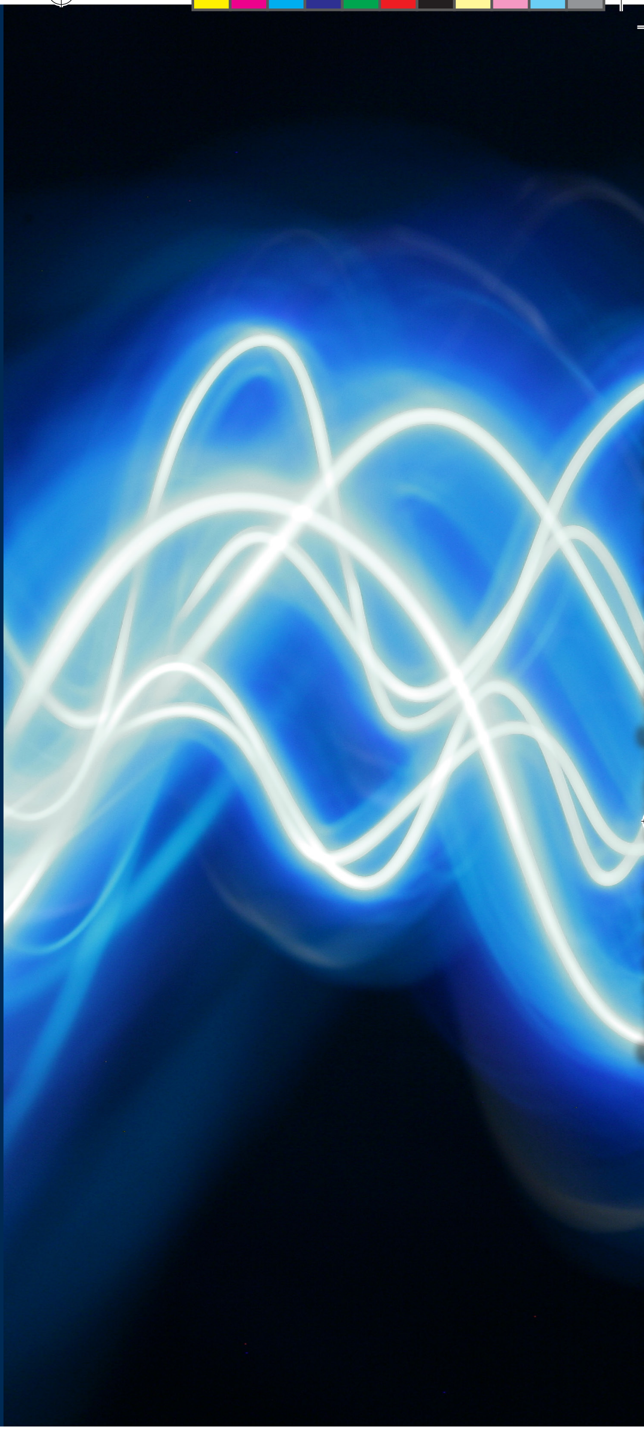
Signal Processing in a Networked Battlespace

Signal processing, the extraction and interpretation of data from sensors, is a critical enabler for decision-making in a variety of domains, such as defence, health, finance, safety and the automotive industry. In recognition of its strategic importance, the UK Ministry of Defence and the Engineering and Physical Sciences Research Council jointly funded a 5-year, £8M academic project starting in 2013. Five years on, this book reports the achievements of that highly successful endeavour. It tracks the impact of a concerted effort to advance the state-of-the-art in fundamental signal processing theory and shows how early consideration of direct links to industry resulted in strong exploitation of the research into industrially-relevant concepts.



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