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Report overview

Association of Intelligence Reports

Introduction

In these report overviews we describe a number of developments concerning the management of large amounts of intelligence reports. These methods use the information conflict between reports as a distance measure in data association and clustering. The methods were initially developed to manage intelligence in anti-submarine warfare but later adopted to ground warfare. This includes work towards integrating fusion methodologies for achieving a dynamic common operational picture in a ground warfare scenario on the tactical level [1]. A simple demonstration is available as [2]. Papers [I-VI] below describe these methods.

Papers I-VI

[I] Schubert, J., On Nonspecific Evidence, *International Journal of Intelligent Systems* 8(6) (1993) 711–725.
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[Online] http://www.foi.se/fusion/fusion11.pdf

In this article we introduce the conflict of Dempster's rule as a distance measure between bodies of evidence. This will serve as a direct measure of any incompatibility of the information between two different intelligence reports. With this measure a criterion for partitioning evidence into subsets is established. This measure is derived as the plausibility of a partition being adequate.

[II] Bengtsson, M., and Schubert, J., Dempster-Shafer clustering using Potts spin mean field theory, *Soft Computing* 5(3) (2001) 215–228.
doi:10.1007/s005000100084
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[Online] http://www.foi.se/fusion/fusion15.pdf

In this article we investigate a problem where belief functions are partitioned into clusters by minimizing the sum of weight of conflict over all clusters. We demonstrate that the weight of conflict can be linearized and mapped to a Potts Spin model. This facilitates efficient numerical solution, even for large problem sizes. Optimal or nearly optimal solutions are found for clustering benchmark tests with a time complexity of $O(n^2 \log^2 n)$.

[III] Schubert, J., Managing Inconsistent Intelligence, in *Proceedings of the Third International Conference on Information Fusion* (FUSION 2000), Paris, France, pp. TuB4/10–16.
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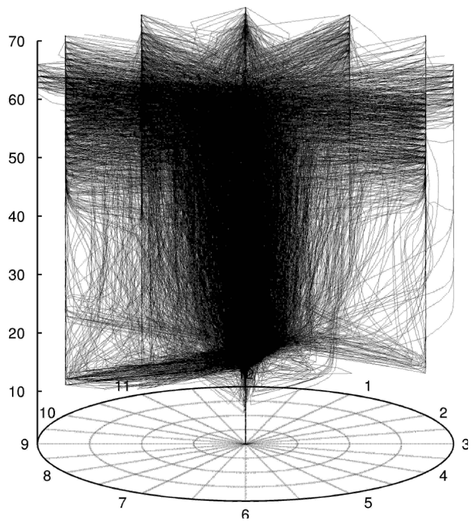
[Online] http://www.foi.se/fusion/fusion14.pdf

In this paper we demonstrate that it is possible to manage intelligence in constant time as a pre-process to information fusion through a series of processes dealing with issues such as clustering reports, ranking reports with respect to importance, extraction of prototypes from clusters and immediate classification of newly arriving intelligence reports. These methods are used when intelligence reports arrive sequentially.



The clustering process of 4095 belief functions into twelve clusters. Top using conflicts only in 66 successive iterations (vertical axis). Below using attractions and conflicts in 33 iterations.

[IV] Schubert, J., Clustering belief functions based on attracting and conflicting metalevel evidence using Potts spin mean field theory, *Information Fusion* 5(4) (2004) 309–318. doi:10.1016/j.inffus.2003.12.002
FOI-S--1414--SE
[Online] http://www.foi.se/fusion/fusion38.pdf

In this article we extend the Potts spin method for clustering belief functions to handle both attractions and conflicts. Attractions are not generated intrinsically in the same way as conflicts. Instead, we assume that it is given from some external source as additional information about the partitioning. The extended method handles both types of evidence internally within all clusters. A significant reduction in classification error rate may be observed when using both.

[V] Schubert, J., Managing decomposed belief functions, in *Proceedings of the Eleventh International Conference on Information Processing and Management of Uncertainty in Knowledge-based Systems* (IPMU 2006), Paris, France, pp. 1428–1435.
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[Online] http://www.foi.se/fusion/fusion46.pdf

In this paper we develop a method for clustering all types of belief functions, in particular non-consonant belief functions. Clustering is here performed by decomposing all belief functions into simple parts that are clustered using Potts spin with both attractions and conflicts. With this method we can manage intelligence reports whose uncertainty is represented as general belief functions with any number of alternative nonspecific propositions. This can be the case when handling human intelligence (HUMINT).

[VI] Schubert, J., and Sidenbladh, H., Sequential clustering with particle filtering – estimating the number of clusters from data, in *Proceedings of the Eighth International Conference on Information Fusion* (FUSION 2005), Philadelphia, USA, paper A4-3. doi:10.1109/ICIF.2005.1591845
FOI-S--1814--SE
[Online] http://www.foi.se/fusion/fusion44.pdf

In this paper we develop a particle filtering approach for grouping intelligence reports into an unspecified number of clusters. The reports arrive sequentially over time. Each cluster corresponds to a potential target from which the reports originate. A potential clustering with a specified number of clusters is represented by an association hypothesis. A set of hypotheses is maintained by sequential Monte Carlo sampling. Compared to earlier information theoretic approaches for finding the number of clusters this approach does not require a large number of trial clusterings, since it maintains an estimate of the number of clusters along with the cluster configuration. The method is suitable for sequential mid sized problems (with respect to number of clusters) when the number of clusters is unknown − in other situations, a non-sequential clustering method is preferred. The method can handle large amounts of data (as long as the number of clusters is not growing).

Benefit

The methods described in these overviews can be used to manage large amounts of intelligence reports in sequential and non-sequential information fusion problems. These include clustering as pre-processing to classification problems, sequential association in multi-target tracking, etc. Some of the methods are implemented in *Anubis* a Swedish Army Intelligence System and *ISFV* a Swedish Air Force Intelligence System [3].

References

[1] Ahlberg, S., Hörling, P., Johansson, K., Jöred, K., Kjellström, H., Mårtenson, C., Neider, G., Schubert, J., Svenson, P., Svensson P., and Walter, J., An information fusion demonstrator for tactical intelligence processing in network-based defense, *Information Fusion,* to appear. doi: 10.1016/j.inffus.2005.11.002

[2] IFD03 demonstration. [Online]. http://www.foi.se/fusion/avi/IFD03_demo.avi

[3] Informationssystem Flygvapnet version 1.0 (IS FV II 1.0A), Swedish Armed Forces, 2002.

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