Pergamon

Vistas in Astronomy Vol. 41, No. 3, pp. 329–335, 1997
© 1997 Elsevier Science Ltd
Printed in Great Britain. All rights reserved
0083-6656/97 $15.00 + 0.00

PII: S0083-6656(97)00035-4

IMAGE FUSION

HENRI MAÎTRE [1], ISABELLE BLOCH
École Nationale Supérieure des Télécommunications, 46 rue Barrault, 75 013 Paris, France

Abstract— We present the main lines along which information fusion has evolved from the first days of data fusion up to image fusion. Then we discuss some of the reasons why image fusion cannot benefit from many of the results of data fusion. In a second part, we present the main tools used to make a fusion of images, and we discuss the fundamentals of these tools. Along the way, we show how important the role of the user is in the design of an appropriate scheme for image fusion. © 1997 Elsevier Science Ltd. All rights reserved.

1. INTRODUCTION

Image processing is becoming one of the most demanding domains for data fusion [17,29,30]. Not only is this true in the classical domains of satellite imaging for remote sensing applications or medical imaging, but also for quality control, military and civilian applications of surveillance, robot vision, vehicle guidance, etc. Whatever the application, image processing evolves in a way where different sensors are asked to contribute to the decision by combining the observations they get on the object of interest.

In this paper we will present first the main lines along which data fusion has evolved up to image fusion. Then we discuss some of the reasons why image fusion cannot benefit from many of the results of data fusion (Section 3). In Section 4, we present some tools used to make a fusion of images, and we discuss the fundamentals of these tools. Along the way, we show how important the role of the user is in the design of an appropriate scheme for image fusion.

2. FROM DATA FUSION TO IMAGE FUSION

The origin of data fusion has to be found in the domain of industrial process control, and especially in the monitoring of factories or production lines. A good example is the monitoring of the production of a chemical product by the continuous integration of the many physical parameters which govern the process: the temperature, pressure, gas consumption, etc. The basic

[1] *E-mail:* maitre@ima.enst.fr.

framework for fusing the pieces of information provided by these sensors is based on a functional model, either explicitly known or implicitly described in a digital simulator, which puts all these measurements into relation. At any moment, having taken into account all the available measurements, a state vector of the production process is deduced, which incorporates current and past data.

Subsequently, similar models have been developed in order to explain and predict more complex systems, like meteorological configurations or ecological systems, by linking into huge models very different contributions made of micro-scale observations (e.g. evapo-transpiration of a canopy), and macro-scale observations (like seasonal variations). Here again physical models are the natural place where fusion of information is made, every measurement playing a precise role in the complex modeling of the whole system. It may happen that some of these measurements are images, when, for instance, a thermal infrared image is used to feed a network of finite elements to solve a propagation system, or a radar image provides information about the water content of the ground when computing a water budget.

But images have been much more important in the third generation of fusion systems which addressed the problem of robot vision, either for autonomous vehicle guidance [1] (video cameras + ultrasonic sensors + lidars or radars), or for the battle-field survey applications where many different sensors located in different places collaborate to ensure the control of a portion of space) [30]. The purpose of sensor fusion in this case is to provide an accurate description of space in terms of geometry and movement, to guarantee a perfect 3D tracking of any object entering the field of view of any sensor, and to predict its trajectory. Therefore the system description often in terms of ballistics or kinematic movement and every detection made by any sensor is to be related to one or several trajectory hypotheses [11,26]. Here again, control theory is the basic framework, and Kalman filtering the most used tool [2], but picture processing is not a major component of the optimization for these problems.

3. IMAGE FUSION VERSUS DATA FUSION

Image fusion came later in the succession of data fusion techniques. Its objective is to use many images of the same scene provided by different sensors in order to provide a complete understanding of the scene, not only in terms of position and geometry, but more importantly, in terms of semantic interpretation. Unfortunately, because of its specificity, it can hardly benefit from the progress of the other fields of data fusion. Let us discuss some of the differences.

(i) Firstly, it is usually futile to look for a global system to encompass in a unique relationship all the components of the image in all possible ways, for instance, with the parameters of an electric power station. The elements of the image obey the physical laws of light/matter interaction (for instance radiometry governs the phenomena in the visible domain, thermodynamics in some parts of the infra-red, electromagnetism for microwaves, etc.) but even when such physical models exist, they only explain local arrangements of pixels and not the global complexity of the scene which is driven by very different hidden rules, like, for instance, geomorphology for middle-scale remote sensing or biology for human-body imaging. In the absence of any possibility to express the relationships between the components of the image into a global explicative formulation, image fusion constrains the user to look for many local and independent interpretations which may or may not be later linked in a loose network of coherence constraints. In the case of astrophysical images, it is not clear that they would escape the general rule, despite the abundant recourse to physical substrate in the image acquisition and interpretation.

(ii) On the other hand, image processing often may use a unique geometrical framework where all the data are put in a relation pixel by pixel. Such are for instance any of the many geocoded reference systems used in cartography, or the standard human body frame in medical imaging, and of course, similar referentials exist in astrophysics and allow us to uniquely define any position or object in space with respect to any observer.

(iii) Finally, image fusion manipulates rather homogeneous data, whatever the sensor. They are made of digital measures, often without absolute significance (except when the sensors have been carefully calibrated), which allow us to access structured information only through rather difficult and uncertain processings, which locally compare adjacent pixels and progressively associate together selected parts of the signal to extract relevant pieces of information. Such processing is more or less identical for every image to be fused and gives image fusion a coherence of treatment which can hardly be found in other domains of data fusion.

4. WHICH TOOLS FOR IMAGE FUSION?

The many different ways to proceed with image fusion have been abundantly described and discussed in the literature. They may be sorted in many different ways [6,8,17]:

- by levels of primitive to be fused which may go from the pixel to the image level with possible fusion at the feature or the object level;
- by localization of the fusion process, close from the sensor, distributed in many sites or centralized;
- by the way data are aggregated: either globally, or sensor by sensor, or theme by theme.

These classifications will not be discussed here, they may be found in other papers [8,17]. We will pay more attention to the general frameworks which have been used for fusing images, and firstly to the different tasks which are necessary in any process of data fusion.

In some cases of specialized applications, expert knowledge exists on the way to combine the data. Sometimes this knowledge proposes a natural guidance through the different images in a well defined order to determine whether such information exists, and thus where to look for the next step [16]. In such circumstances the fusion scheme is very much like a decision tree which may be efficiently ruled by a Knowledge Based System, as is for instance the case in [21,10]. These favorable situations are not many and often result from a well-established protocol which guarantees the quality and the repeatability of the acquisitions. We will be concerned in the following lines by the only numerical fusion techniques where information is more evenly distributed [20] and obliges the user to track the evidence in many different data planes to allow for an ultimate detection. How are these pieces of evidence detected and how are they combined?

4.1. *Information extraction from images*

It may happen that the pixel value as issued from the sensor provides enough evidence to the presence or absence of an object. In this case, this pixel value may be directly used in the fusion process. But very often detectors are used to better guarantee the presence of the object. They make use of the pixel itself and its neighboring pixel to determine for instance a contrast, or a geometrical configuration which sustains the presence of the object, or, on the contrary, invalidates this hypothesis. For the sake of simplicity, we imagine that for every possible hypothesis H_i (an hypothesis is for instance the presence of a given class at a given position) we are able to get such information for any image j. This valued is called the measure of i in the image j

and we denote it by m^i_j. From the whole set of measures $\{m^i_j\}$ for all i, all j, for each and every pixel, the decision is to be taken.

Very often the decision is taken for one pixel without reference to the others. This may be relevant when the problem is stationary and non-context dependent. The recourse to larger features or the choice of the detector may allow to transform a "context-dependent" problem into a context-independent one in some cases. When a classification technique explicitly takes into account the neighboring sites, it is called a contextual classification method. This is for instance the case of Markov Random Fields (MRF) and relaxation techniques [15].

4.2. *The three stages of image fusion*

We consider now only context-independent decisions and come to the problem of fusion. We have a complete table of measures m^i_j for every pixel (or every area) and we want to decide for one hypothesis H_i. How is this possible?

Three stages are needed:

(i) Transform the measures in such a way that one is allowed to combine them. This stage is the modeling of the problem where one has to choose a theoretical framework with acceptable properties, and inside this framework a convenient representation of the data (for instance, within probability theory, model the signal as a Gaussian Markov process).

(ii) Combine the data as transformed by the representation according to the allowed rules for the chosen framework (for instance the Bayes rule). If many rules are possible, choose the best one for the problem.

(iii) From the resulting combination take a decision in agreement with the problem. Here again many rules are possible (for instance one may prefer the maximum a posteriori or the maximum likelihood).

We see from the previous lines how important the choice of the frame of representation is. Several such frames exist which have been created to manipulate measures and information.

The best known is the theory of probabilities within the Bayesian framework. Although it may appear at the end of the 20th century as a definite and absolute theory, it only emerged after many decades of intense and uncertain struggles against different variants which presented many advantages that it is no longer reflecting [7]. Even in its present form, probability is a single expression to cover several conceptions of the world that are hardly compatible (see for instance the Introduction in Ref. [18]). Probability theory offers today an exceptionally broad body of theorems, rules, criteria, tests, and concepts to cover most of the aspects of information processing. As soon as one can reliably go from the measure m^i_j to a probability, the fusion problem finds an explicit solution in probability theory.

Is this solution acceptable? There are two reasons to have doubts about it. Firstly, the step from measure to probability is often difficult to establish; when put into the probabilistic frame, the fusion problem is only solved if we may provide the right information at every stage of the probabilistic decision. This information is often impossible to determine, such as for instance the priors for some classes (and even for some problems, have priors any meaning?), or the conditional dependence between some variables. Because of the difficulty to provide all the necessary information to make probability theory optimally work, experience has shown that the practical results provided by probability theory are sometimes poor and often heavily depending on practical implementation, such as for instance the definition of learning sets. In the Bayesian probability framework, the modeling stage is rather constraining, the combining rule is fixed by the Bayesian rule. On the contrary, the decision rules are many (maximum a posteriori, maximum expectation, etc.). From the richness of the decision rules, people usually say that the probabilistic approach may guarantee the best optimal solution, for any criterion one states. This affirmation has of course to be moderated, since it does not take into account all the other possible associations of information which could have been made if the only probabilistic framework would not have been fixed.

But the advantages of probability data fusion are many. They have been experienced many times and it still remains the most widely used way of modeling image fusion.

Fuzzy set theory [32] is the counterpart of probability theory. It provides a very intuitive modeling which may be easily accepted, all the more since it puts almost no constraint on the data to be combined [12]. Moreover, the way to associate information in fuzzy set theory is not constrained to the Bayes rule as in probability theory. One may choose many different combination rules which could reflect one's knowledge about how information has to be combined. Many solutions have been discussed in Refs. [13,31,14,4], which provide a first step towards a more complete theory of fuzzy decision.

In the case of evidence theory [27,28], the choice has been made to use more than one single piece of information to represent the measure (and the associated knowledge) in the fusion stage. This allows one to associate (as in possibility theory [33,14]) with any measure the two concepts for instance of uncertainty and imprecision which are coded together in probability theory or in fuzzy set theory. Furthermore, it makes it very easy not only to process information on a given class, but also on the disjunction of many classes which are not distinguished for instance by one sensor [5,9,19,23].

From these three examples chosen among the many possible ways to combine information from different sources [22], we see where the role of the user is, in definitively choosing the best representation to adhere to the knowledge he/she has on the problem to be solved.

5. CONCLUSION

Obviously, image fusion is still in its infancy. If some impressive results are not yet available, further work is needed. One of the major achievements until now is to adapt several theories, generally arising from other fields (in particular artificial intelligence) to the needs of image fusion. Several studies have been carried out in order to find a proper modeling of image fusion problems in these frameworks, for instance to estimate conditional probabilities, fuzzy membership functions or belief functions from image information. What is still missing is the inclusion of image processing techniques into the fusion schemes, in order to deal with the specific aspect of image information, including its spatial nature.

References

[1] M.A. Abidi, R.C. Gonzalez, *Data Fusion in Robotics and Machine Intelligence* (Academic Press, New York, 1992).

[2] Y. Bar-Shalom, T.E. Fortmann, *Tracking and Data Association* (Academic Press, San Diego, 1988).

[3] J.C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms* (Plenum, New York, 1981).

[4] I. Bloch, Information Combination Operators for Data Fusion: A Comparative Review with Classification, *IEEE Trans. on Systems, Man, and Cybernetics* **26** (1996) 52.

[5] I. Bloch, Some Aspects of Dempster-Shafer Evidence Theory for Classification of Multi-Modality Medical Images Taking Partial Volume Effect into Account, *Pattern Recognition Letters* **17** (1996) 905.

[6] I. Bloch, H. Maître, Fusion de données en traitement d'images: modèles d'information et décisions, *Traitement du Signal* **11** (1994) 435.

[7] I. Bloch, Incertitude, imprécision et additivité en fusion de donées: point de vue historique, *Traitement du Signal* **13** (1996) 267.

[8] I. Bloch, H. Maître, Fusion of Image Information under Imprecision, In: *Aggregation of Evidence under Fuzziness*, B. Bouchon-Meunier, ed., Series Studies in Fuzziness (Springer, Berlin, 1997).

[9] S.Y. Chen, W.C. Lin, C.T. Chen, Evidential Reasoning based on Dempster-Shafer Theory and its Application to Medical Image Analysis, In: *SPIE* **2032** (1993) 35.

[10] V. Clment, G. Giraudon, S. Houzelle, Interpretation of Remotely Sensed Images in a Context of Multisensor Fusion, In: *ECCV 92*, Santa Margherita Ligure, Italy, May 1992, p. 815.

[11] B.V. Dasarathy, Fusion Strategies for Enhancing Decision Reliability in Multi-Sensor Environments, *Optical Engineering* **35** (1996) 603.

[12] D. Dubois, H. Prade, *Fuzzy Sets and Systems: Theory and Applications* (Academic Press, New York, 1980).

[13] D. Dubois, H. Prade, A Review of Fuzzy Set Aggregation Connectives, *Information Sciences* **36** (1985) 85–121.

[14] D. Dubois, H. Prade, Combination of Information in the Framework of Possibility Theory, In: M. Al Abidi et al., eds., *Data Fusion in Robotics and Machine Intelligence* (Academic Press, New York, 1992).

[15] S. Geman, D. Geman, Stochastic Relaxation, Gibbs Distribution and the Bayesian Restoration of Images, *IEEE trans. on Pattern Analysis and Machine Intelligence* PAMI-6 (1984) 721.

[16] S. Houzelle, G. Giraudon, Automatic Feature Extraction Using Data Fusion in Remote Sensing, In: *SPIE* on Sensor Fusion, Boston, November 1991.

[17] *Proceedings of the IEEE*, Special Issue on Image Fusion January 1997.

[18] E.T. Jaynes, *Probability Theory: The Logic of Science*, http://bayes.wustl.edu, Introduction, 1997.

[19] S. Mascle, I. Bloch, D. Vidal-Madjar, Unsupervised Multisource Remote Sensing Classification using Dempster-Shafer Evidence Theory, In: *SPIE/EUROPTO Conference on Image and Signal Processing for Remote Sensing*, Vol. 2579, Paris, France, September 1995.

[20] H. Maître, Entropy, Information and Image, In: H. Maître and J. Zinn-Justin, eds., *Progress in Picture Processing, Les Houches Session LVIII* (Springer, Berlin, 1996) p. 881.

[21] D. McKeown, W. A. Harvey, J. McDermott, Rule-Based Interpretation of Aerial Imagery, *IEEE Trans. on Pattern Analysis and Machine Intelligence* **7** (1985) 570.

[22] La Somb, Raisonnements sur les informations incomplètes en intelligence artificielle, Teknea, Marseille 1989.

[23] M. Ménard, E.H. Zahzah, A. Shahin, Mass Function Assessment: Case of Multiple Hypotheses for the Evidential Approach, In: *Europto Conf. on Image and Signal Processing for Remote Sensing*, Taormina, Italy, September 1996.

[24] H. Moissinac, H. Maître, I. Bloch, Markov Random Fields and Graphs for Uncertainty Management and Symbolic Data Fusion in a Urban Scene Interpretation, In: *SPIE/EUROPTO Conference on Image and Signal Processing for Remote Sensing*, Paris, France, September 1995.

[25] J. Pearl, Fusion, Propagation, and Structuring in Belief Networks, *Artificial Intelligence* **29** (1986) 241.

[26] N.S.V. Rao, S.S. Iyengar, Distributed Decision Fusion under Unknown Distributions, *Optical Engineering* **35** (1996) 617.

[27] G. Shafer, *A Mathematical Theory of Evidence* (Princeton University Press, Princeton, 1976).

[28] P. Smets, The Combination of Evidence in the Transferable Belief Model, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-12 (1990) 447.

[29] Optical Engineering, Special Section on sensor Fusion, 35 (1996).

[30] Optical Engineering, Special Section on sensor Fusion, 36 (1996).

[31] R.R. Yager, Connectives and Quantifiers in Fuzzy Sets, *Fuzzy Sets and Systems* **40** (1991) 39.

[32] L.A. Zadeh, Fuzzy Sets, *Information and Control* **8** (1965) 338.

[33] L.A. Zadeh, Fuzzy Sets as a Basis for a Theory of Possibility, *Fuzzy Sets and Systems* **1** (1978) 3.