DATA FUSION IN 2D AND 3D IMAGE PROCESSING: AN OVERVIEW

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Abstract. This paper presents an overview of the current state of the art in image fusion, with an emphasis on the emergence of new techniques, often issued from other domains like artificial intelligence and uncertainty modeling. We address the two following points: firstly the aim of data fusion and its specificity when image information has to be combined, with emphasis on the respective roles of numerical and symbolic information, vs. numerical and symbolic types of treatment, secondly the theoretical frameworks for modeling imprecision and uncertainty (probability, fuzzy sets, belief functions). The main steps of image fusion are illustrated in a simple example in 3D medical image fusion.

1 Introduction

The need for data fusion in image processing increases in relation to the increase of acquisition techniques. These techniques are more and more jointly used to give access to a better knowledge in many cases of experimental sciences. In image processing, data fusion appears as a necessary stage for applications like medical imaging, aerial and satellite imaging, quality control, robot vision, vehicle or robot guidance.

Instead of focusing on the system aspects (architecture and design) as often in data fusion, we define image fusion as the process that combines information issued from different sources in order to take a decision [7]. Therefore we focus on techniques for combining information towards a specific goal. This process aims at improving the decision that could have been taken from partial information by gathering several sources, data or pieces of knowledge, achieving a better understanding of the observed phenomenon. This definition of data fusion excludes all domains where the pieces of information are not really combined in order to improve decision, like registration, color composition of multi-source images, visualization, etc. We also assume here the most general case of heterogeneous information, i.e. where no metrics can be defined among sources, therefore excluding the classical data analysis methods [11] based on vectorial representations of data in an appropriate metric space.

Early works in image fusion may be tracked in the first applications where several images or sources of data where used, often without using the term "data fusion", the processing taking a simple algorithmical form. Then more formalized rule-based systems appeared (see e.g. [16]), where the processing of one image depends on the results of some processing applied on another image, these links being driven by rules. However all-or-nothing techniques like in standard rule-based systems have difficulties to face the problems due to the inherent imperfection of image information (imprecision, uncertainty). Therefore numerical approaches for dealing with this imperfection in image fusion have been developed. We will restrict this paper to these approaches, the use of which is more recent in image processing.

We first present a short discussion about symbolic and numerical fusion in Section 2. Then we describe the main specificities of image information when dealing with a fusion problem in Section 3. In Section 4, we give a short overview of the main numerical fusion methods, that are increasingly developed in image fusion. We specify these methods in Section 5, by illustrating the different steps on a real image fusion problem, taken from the medical imaging domain.

2 Symbolic vs. Numerical

There have been large discussions in the fusion community about the duality between numerical and symbolic fusion. Our aim here is not to go deeply in this discussion but rather to present the different levels at which this question may be addressed. Since most of the discussions originate from the fact that the concepts are confusing if this level is not specified, this type of presentation may help to clarify these concepts. The three levels at which we would like to make a distinction between numerical and symbolic are (i) the type of data to be treated, (ii) the type of processing applied to these data, (iii) the role of representations.

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2.1 Data and information

By numerical information, we mean data directly given as numbers. These numbers may represent various features, typically physical measures, grey levels, response to an image processing operator, etc. They may be directly read from the images to be fused, or attached to the domain or contextual knowledge (e.g. wave lengths in satellite imaging, acquisition times in medical imaging, etc.).

By symbolic information, we mean all information given as symbols, propositions, rules, etc. Such information can be related to the data to be combined (e.g. graphical information in a map or in an anatomical atlas, attributes computed on data or objects previously extracted from the images) or related to the domain knowledge (e.g. propositions about the properties of the problem at hand, structural information stating for instance that a road network can be represented as a graph using roads and crossroads, propositional knowledge stating general rules about the scene like "the ventricles are always inside the white matter", etc.).

The classification of data and information in symbolic and numerical classes cannot always be done in a crisp way. We may have to deal with "hybrid" kind of information, where numbers are used for coding information that is not necessarily of numerical nature. This is typically the case for the evaluation of some data or treatment, for the quantification of imprecision or uncertainty. In such cases, the absolute values of these numbers are not important, this is rather the ranking which plays an important role. These numbers may be attached to symbolic information as well as to numerical information. In image processing, examples can be found for quantifying the quality of a detector, the evaluation of some symbolic data, of source reliability, of confidence in some measurement or numerical value, etc.

2.2 Processing

As far as processing of information is concerned, we mean by numerical treatment any computation on numbers. In data fusion, it concerns approaches that combine numbers by some formal calculus. Note that such kind of treatment does not make any assumption on what kind of data is represented by numbers. Data may be originally of numerical as well as of symbolic nature.

Symbolic types of treatment include formal computation on propositions (logic is but one example), possibly taking into account numerical knowledge. Structural approaches, like graph-based approaches often used in structural pattern recognition, can be considered as belonging to this class.

We consider as hybrid types of treatment the methods where prior knowledge is used in a symbolic way to control numerical treatments, for instance by stating some propositional rules that suggest/allow/prevent specific numerical operations. Typically, a proposition stating in which cases sources A and B are independent can be used in the way probabilities are combined, or knowing that the recognition depends only on some local or contextual knowledge may lead to an appropriate modeling of the scene as a Markovian field. Such kind of hybrid processing is widely used in image processing and image fusion.

2.3 Representations

As it appears from the two previous subsections, the representations and their type may play very different roles. Numerical representations can be used for intrinsically numerical data as well as for evaluation and quantification of symbolic data. An important use of numerical representations in data fusion is for quantifying imprecision, uncertainty or reliability of the information (this information may be of numerical as well as of symbolic nature), therefore representing rather information about the information than the data themselves. We will focus on such kind of representations in the description of the main numerical approaches for image fusion. Numerical representations are also often used for degrees of belief attached to numerical and/or symbolic knowledge, and for degrees of consistency or inconsistency in a database. Note that the same (numerical) formalism can be used for representing very different kinds of data or knowledge: the most obvious example is the use of probabilities for representing data as different as frequencies, subjective beliefs, etc. [2].

Symbolic representations can be used in logical systems, or knowledge-based systems, but also as prior knowledge for guiding numerical treatment, as a structural support for image fusion (see e.g. [17]), and of course as semantics attached to the manipulated objects.

In several examples, a strong duality can be observed between the roles of numerical and symbolic representations. Let us take the example of a map and an aerial image of the same area. The numerical information carried by the image provides a quite accurate description of the scene, but the interpretation attached to it is hard to derive. For instance, it is generally difficult to assess the type of a building, although its drawing on the image is accurate. On the contrary, the map carries symbolic information as a semantic meaning of the objects represented on the map but its shape is often sketchy. This duality has been exploited in heterogeneous image fusion e.g. in [17].

3 What should be taken into account in image fusion?

In image fusion, information is typically provided by several "images" or aspects of a scene. They may come from different sensors, obtained using different imaging techniques or with different acquisition parameters or at different times. Although most of the methods described below are originated from other fields than image processing, applying them to image fusion calls for adaptations that take into account the specificities of the data involved in image fusion schemes.

The pieces of information that are involved in a fusion process can be of very different natures. We distinguish the data which constitute the information to be actually combined, and the additional knowledge that is used to help the combination or to impose some constraints on it. This includes information about information to be combined (e.g. source reliability) and knowledge related to the context or the domain. Similar distinctions can be made between factual knowledge (e.g. what is really observed in the images) and general knowledge (e.g. domain knowledge).

The information to be combined is never perfect (otherwise fusion would not be necessary). This imperfection can take several forms, including mainly imprecision, uncertainty, ambiguity, incompleteness. Distinction between imprecision and uncertainty along with illustrative examples can be found e.g. in [8], and more specifically for image processing in [7]. The aim of data fusion can be expressed as a way to deal with all these kinds of imperfection by exploiting the multiple source data, and more precisely two main factors: one is the partial redundancy of data, since all sources provide information about the same phenomenon, the other is the complementarity between data since each source provides a different point of view about the phenomenon. Complementarity concerns the information itself (one object can be seen in a range image while it will be hidden in another one), as well as the type of information (e.g. in brain imaging, one source may provide anatomical information, while another may provide functional information) and the accuracy and quality of information (e.g. two different images of the same type but acquired with different parameters may be of different quality for different structures). Redundancy can be used in order to increase the global information, and complementarity in order to improve certainty and precision. The decision is thus improved by the fusion in terms of both quantity and quality.

Other characteristics in image fusion are the heterogeneity of data and their complexity. Several imaging techniques have to be used together to answer a specific question. They provide different aspects and different points of view on the problem by exploiting different physical properties. For instance when planning some surgical operation in medical imaging, the necessary data can be as heterogeneous as anatomical images (provided by MRI or CT), angiographic images (MRA, spiral CT, etc.), functional signals (EEG, MEG) or images (PET, functional MRI). These images are not informative about the features they are not dedicated to. Similar examples can be found in other domains. An additional cause of heterogeneity comes from the fact that image information needs to be combined with external information to make sense (information about information and domain or context knowledge). Complexity of the information is partly due to the previously mentioned characteristics but also to the increasing number of acquisition techniques and to the huge data sets that have to be dealt with. Typically, one MRI brain image contains $256 \times 256 \times 128$ voxels, one satellite image contains 6000×6000 pixels, and several images of this size have to be combined in a fusion process. The large data volumes, and the statistical measures that are therefore made possible, may explain the use of statistical approaches in most image fusion systems. The complexity of the fusion process also comes from the simultaneous redundancy and complementarity between images, closely related to the heterogeneity aspects.

4 Main numerical approaches for dealing with imprecision and uncertainty in data fusion

In this Section, we present three main numerical approaches used in image fusion (Bayesian fusion, Dempster-Shafer evidence theory, and fuzzy approaches). We just summarize here the basic principles of these methods. Their instantiation for the specific case of image information fusion will be addressed in the next Section.

4.1 Problem statement

We will restrict ourselves here on a centralized point of view, where all pieces of information are available simultaneously. Other possible schemes are described e.g. in [7, 6]. A general signal or image fusion problem can be stated in the following terms: given l images or more general sources I_j representing heterogeneous data on the observed phenomenon, take a decision D_i on an element x, where x can be a pixel or any other higher level object extracted from the signals or images (see e.g. [7] for the fusion levels), and D_i belongs to a decision space $D = \{D_1, ..., D_n\}$ (or set of hypotheses). In numerical fusion methods, the information relating x to each possible decision D_i according to each image I_j is represented as a number M_i^j having different properties and different meanings depending on the mathematical fusion framework. In the centralized scheme, the measures related to each possible decision i and provided by all sources are combined in a global (still numerical) evaluation of this decision, taking the form, for each i: $M_i = F[M_i^1, M_i^2, ..., M_i^l]$, where F is a fusion operator. Then a decision is taken from the set of $M_i, 1 \leq i \leq n$. In this scheme, no intermediate decision is taken and the final (binary) decision is issued at the end of the processing chain. Therefore we avoid to take decisions at intermediate steps with partial information only, and thus we diminish contradictions and conflicts, which usually require a difficult control or arbitration step.

The main steps of image fusion can be therefore described as:

1. modeling image information and its imperfection (imprecision, uncertainty, ambiguity),
2. estimation of the $M_i^j, 1 \leq i \leq n$ according to the chosen mathematical framework,
3. combination, i.e. choice of an appropriate fusion operator F [3],
4. decision.

4.2 Bayesian approach

The most used framework in signal and image fusion is undoubtedly the probabilistic framework, and in particular Bayesian approaches to which we will restrict our presentation.

In the Bayesian framework, the M_i^j's represent conditional probabilities: $p(x \in D_i | I_j)$.

The combination of information as well as of prior probabilities is then performed through the Bayes theorem. Bayesian methods are probably the most widely used in probabilistic image fusion. They lead mainly to conjunctive data fusion. Other probabilistic techniques have been proposed, that are able to model different kinds of fusion logic (e.g. [18]).

The most used decision rule in Bayesian decision is the maximum a posteriori. However, many other criteria have been developed by probabilists and statisticians, including maximum posterior marginal, maximum likelihood, maximum entropy, minimum expected risk, etc.

4.3 Dempster-Shafer evidence theory

Dempster-Shafer evidence theory (DS) allows to represent both imprecision and uncertainty, using plausibility and belief functions derived from a mass function defined on 2^D rather than on D only [19, 20]. This is one of the main advantages of the DS approach.

In the DS framework, masses are combined by the orthogonal rule of Dempster [19]. For m_j being the mass function associated with source j ($j = 1, 2$), this rule is written, for any subset A of D (similar equations are defined for l sources):

$$(m_1 \oplus m_2)(A) = \sum_{B_1 \cap B_2 = A} m_1(B_1) m_2(B_2). \qquad (1)$$

This type of combination, which is not idempotent, assumes cognitive independence between sources rather than statistical independence (see [6]). Similar equations can be derived for directly combining belief or plausibility functions. The combination can be normalized by $1 - k = 1 - \sum_{B_1 \cap B_2 = \emptyset} m_1(B_1) m_2(B_2)$. To some extent, k can be interpreted as a measure of conflict between the sources. It is very important to take this value into account for evaluating the quality of the combination: when it is high (in case of strong conflict: $k \approx 1$), the combination may not make sense and may lead to questionable decisions. Several authors prefer not to normalize the combination result (see e.g. [20]).

After the combination, the final decision is usually taken in favor of a simple hypothesis using one of several rules: for instance, the maximum of plausibility (generally over simple hypotheses), the maximum of belief, the maximum of belief without overlapping of belief intervals, i.e. in favor of $d \in D$ such that $Bel(d) \geq \max_{d' \in D, d' \neq d} Pls(d')$ (a very strict condition), the pignistic decision rule [20], or rules using expected utility.

4.4 Fuzzy sets and possibility theory

In the framework of fuzzy sets and possibility theory [23, 24, 8], the M_i^j's represent membership degrees to a fuzzy set or possibility distributions.

For the combination step in the fusion process, the advantages of fuzzy sets and possibilities rely in the variety of combination operators, which may deal with heterogeneous information [9, 22, 10]. We proposed a classification of these operators with respect to their behavior (in terms of conjunctive, disjunctive, compromise [9]), the possible control of this behavior, their properties and their decisiveness, which proved to be useful for several applications in image processing [3]. It is of particular interest to note that, unlike other data fusion theories (like Bayesian or Dempster-Shafer combination), fuzzy sets provide a great flexibility in the choice of the operator, that can be adapted to any situation at hand.

Decision is usually taken from the maximum of membership values after the combination step. Constraints can be added to this decision, typically for checking for the reliability of the decision (is the obtained value high enough?) or for the discrimination power of the fusion (is the difference between the two highest values high enough?).

5 Instantiating numerical approaches when dealing with an image fusion problem

In this Section, we provide some hints on how to apply the previous approaches to image fusion problems and illustrate this on an image fusion example in medical imaging. The aim of this example is to combine dual-echo brain MR images in order to provide a classification (which is a typical decision problem) of the brain into 3 classes: brain, ventricles and cephalo spinal fluid (CSF), and pathology. These images are shown in Figure 1 (only one slice of the 3D brain volume is shown).

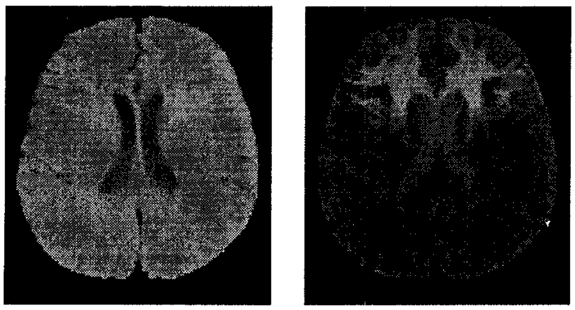

Figure 1: Dual echo MR image of the brain, showing three main classes: brain, ventricles and pathology (the white area on the right image).

5.1 Modeling

The main objective at this step is to define the set D. This is most often defined in a supervised way, according to the general decision objective (as in the example presented here). Some work try to find D in a unsupervised manner, e.g. using unsupervised classification techniques as in [15].

In the Bayesian franework, due to the difficulty to learn joint distributions in image processing, independence between sources is often assumed, which is also part of the modeling step.

In the DS framework, the focal elements have also to be chosen. Indeed, it leads to a very flexible and rich modeling, able to fit a very large class of situations, occurring in particular in image fusion. A few examples of situations where DS theory may be successfully used are described in [4]. To our opinion, one of the main differences between DS and fuzzy sets lies at the level of flexibility. These different situations are easily taken into account in the DS framework at the modeling level, while in the fuzzy set framework this flexibility relies on the wide range of available combination operators.

In the fuzzy set framework, one possible model consists in setting, for each element x, $M_i^j(x) = \mu_i^j(x)$, where $\mu_i^j(x)$ denotes the membership degree of x to the class i according to image j. Another model consists in interpreting $M_i^j(x)$ as a possibility degree that x belongs to class j, and therefore setting $M_i^j = \pi_i^j$, where π_i^j is a possibility distribution according to image j. Such models explicitly represent imprecision in the information provided by the images, as well as possible ambiguity between classes or decisions. Fuzzy sets have several advantages for representing imprecision inherent to the type of data and problems we may have in signal and image processing. First, they are able to represent several types of imprecision. Second, information can be represented at different levels with fuzzy sets (local, regional, or global), as well as under different forms (numerical, or symbolic). Third, the fuzzy set framework allows for the representation of very heterogeneous information, and is able to deal with information extracted directly from the images, as well as with information derived from some external knowledge, like expert knowledge for instance.

5.2 Estimating

In the probabilistic framework, the probabilities involved in the model are computed from characteristics extracted from the data, typically signal intensity, grey-levels or texture indices at low level, or other features and object properties at higher level. They represent mainly the probabilistic uncertainty attached to image information. One of the advantages of Bayesian fusion relies on the large experience on learning that allows the user to perform estimation of these conditional probabilities. This is why estimation in the other theories often rely on probabilistic methods. Another advantage of probability originates from the notion of entropy, of conditional entropy and of mutual information [12, 13, 14]. They can be efficiently used in order to assess the complementarity and redundancy between images at any level of representation (see e.g. the example in [21]).

The definition of mass functions in DS theory remains a largely unsolved problem, which did not yet find a general answer. In image processing, they may be derived at three different levels. At the highest, most abstract level, information representation is used in a way similar to that in artificial intelligence and masses are assigned to propositions. At an intermediate level, masses are computed from attributes, and may involve simple geometrical models. At the pixel level, mass assignment is inspired from statistical pattern recognition. The most widely used approach is as follows: masses on simple hypotheses are computed from probabilities or from the distance to a class center. Then a global ignorance $m(D)$ is introduced as a discounting factor, often as a constant on all pixels. This approach strongly limits the power of DS. A few methods have been proposed to overcome this limitation. The reader may refer to [4] for more details and references about this step.

Similar problems occur for defining membership functions or possibility distributions. Most methods rely on some transformations from probabilities (estimated from histogram) to possibility distributions. However, this causes severe interpretation problems. Typically, a pixel having a value which has a low occurrence frequency in the image may belong completely and without ambiguity to one class. This is generally not taken into account by methods that try to produce membership functions shaped as modes in the histogram. In [5], we propose a completely unsupervised method, based on criteria accounting for both the distance between distributions and for constraints on their shape, which is able to estimate all class membership functions simultaneoulsy. This method has been applied for estimating the membership functions for the 3 classes on both images of the example of Figure 1. The result for one image is given in Figure 2.

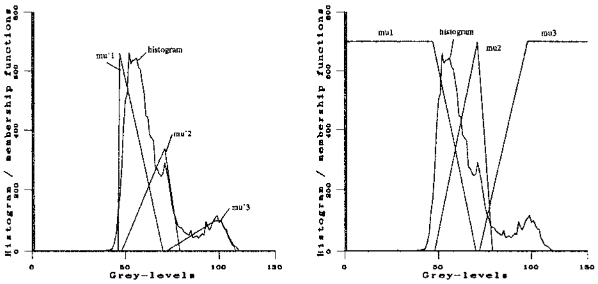

Figure 2: Result of the estimation of three classes (first step: estimation according to histogram only; second step: deriving μ_i by introducing a priori information on the function shapes) on the second image of figure 1.

5.3 Combining

In Bayesian and evidential fusion, the user is entirely guided by the formalism at this step (except for the independence problem already mentioned). On the contrary in fuzzy fusion, he is in charge of choosing the operator adapted to the situation at hand. Indeed, image fusion has often to deal with situations where a source of information is reliable only for some classes, or does not provide any information about some class, or is not able to discriminate between two classes while another does. In this context, some operators are particularly powerful, like operators that behave differently depending if the values to be combined are of the same order of magnitude or not, if they are small or high, and operators that depend on some global knowledge about source reliability about classes, or conflict between images (global or related to one particular class) [10]. The combination process can be done at several levels of information representation, from pixel or low level to higher level. Whatever the level of representation, such a process corresponds to a numerical approach. A noticeable advantage of this approach is that it is able to combine heterogeneous pieces of information. Another scheme relies on a symbolic approach and consists in combining information extracted from images but not directly attached to pixels or regions. This is typically used for combining rules where the rule elements involve fuzzy attributes, fuzzy measures or fuzzy relationships.

The following paragraphs present the reasoning process and the combination results on the example, where fusion is performed at the pixel level.

Markovian fusion: A first fusion scheme has been developed in the framework of Markov random fields. It consists in combining in a conjunctive way information provided by both images and a regularization term (see [1] for more details on the fusion algorithm). Here, we define the potential functions used in the energy to be minimized as the fuzzy complementation of the estimated membership functions (i.e. a high membership value corresponds to a low energy and conversely). The results are shown in Figure 3.

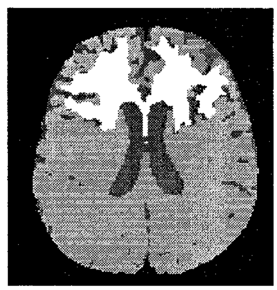

Figure 3: Classification result obtained using a Markovian method (see [1]).

Fuzzy fusion: We use the results obtained with the automatic estimation of membership functions for combining these functions with fuzzy operators. Since both images provide similar information about the ventricles, we use a mean operator to combine the membership functions obtained in both images for this class. Brain and pathology cannot be distinguished in the first echo and we obtain only one class for this image, denoted by μ_c^1. In the second image, we obtain two classes denoted by μ_c^2 and μ_{path}^2 respectively. We combine μ_c^1 and μ_c^2 using an arithmetical mean again. As for the pathology, we combine μ_c^1 and μ_{path}^2 using a symmetrical sum defined as: $\frac{ab}{1-a-b+2ab}$. This guarantees that no pathology is detected in the areas where $\mu_{path}^2 = 0$, and this reinforces the membership to that class otherwise, in order to include the partial volume effect areas in the pathology (this corresponds to what radiologists do). After the combination, the decision is made according to the maximum of membership values. The result is shown in figure 4.

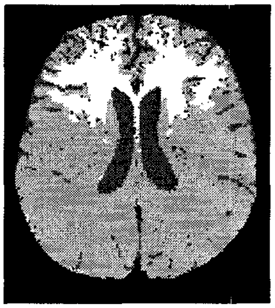

Figure 4: Final decision after fuzzy combination (note that the decision is taken at each pixel individually, without spatial regularization).

Dempster-Shafer fusion: Finally, we interpret the results of the automatic estimation as mass functions and combine them in the framework of Dempster-Shafer evidence theory [19]. We exploit an important feature of this theory that allows for a very flexible modeling of the situation at hand and does not force the introduction of information not contained in the images [4]. We do not assign any mass to the brain and to the pathology in the first image since it does not discriminate these classes, but we assign μ_c^1 to the union of these two classes. The ambiguity will then be solved through the combination. The mass functions for the two images are combined using Dempster rule of combination, and decision is taken according to the maximum of belief. The result is shown in figure 5.

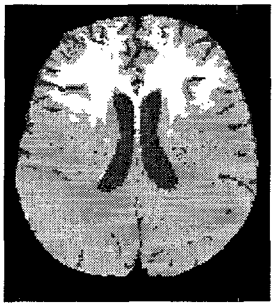

Figure 5: Dempster-Shafer fusion: result of decision after combination with Dempster rule (the results are quite similar to those obtained by fuzzy fusion, and better in the areas affected by partial volume effect around the pathology).

5.4 Deciding

In image fusion, very few works addressed the decision problem in DS and fuzzy approaches, unlike in probabilistic approaches, and very few tools allow to take refined decisions. In the above example, a simple decision according to the maximum of membership has been used.

An interesting feature of simple decision schemes is that spatial information can be introduced at the last step, by refining decision by considering local results of the combination around each point. Note that in fusion systems working at hugher level (geometrical features or objects), the spatial information is implicitly taken into account during the whole process.

5.5 Some links between these steps

Although the different steps have been presented quite independently, it is obvious that there exist some links between them. The modeling step depends on both the final decision objective and on what we are able to estimate (the example illustrates this in the case of DS). The estimation depends on the combination framework: in Bayesian fusion, we have to estimate all classes, but this is not necessary in DS. In fuzzy fusion, this problem can be often overcome by simple supervised rules, as shown on the example. Combination and decision are strongly linked in DS, in particular if the normalized combination rule is used. Since the DS fusion operator has a conjunctive behavior, we claim that this means that all imprecision on the data has to be introduced explicitly at the modeling level, in particular in the choice of the focal elements. For instance, ambiguity between two classes in one image has to be modeled using a disjunction of hypotheses, so that conflict with other images can be limited and ambiguity can be possibly solved during the combination.

Several other examples of links between the main steps of the fusion process can certainly be established, showing that it is very difficult to handle them separately.

5.6 Evaluation

Evaluation is one of the most critical problem. When comparing approaches, the literature shows very contradictory conclusions. This is undoubtedly a proof that a lot of research is still needed in image fusion before definite conclusions can be drawn, and that the field is still not completely mastered.

Another point is that one of the main problems in image fusion is that it is very difficult to access the truth (in particular in medical imaging), making evaluations often subjective.

6 Conclusion

One of the main observations that can be made from the recent literature in image fusion is that research teams have acquired now a better understanding of the methods and of how they can be used in image fusion. Non-probabilistic methods are getting more and more popular, and there main features are better exploited, not just by mimicking probabilistic methods.

One aspect that still needs a lot of development is a better management of spatial information. This is naturally taken into account in Bayesian fusion in the Markovian setting, but it still remains at very simple stages in fuzzy and evidential fusion when working at low level. Some attempts have already been made, e.g. using fuzzy morphology (see [7]).

Concerning applications, most of them deal with 2D images, in different domains. 3D applications are more seldom. This is mainly due to the additional complexity related to the huge data sets and the increased complexity of spatial information (topology, homotopy, etc.).

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