CHOQUET INTEGRAL PARAMETER OPTIMIZATION FOR A FUSION SYSTEM DEVOTED TO IMAGE INTERPRETATION

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Abstract.
Parameter adjustment of a fusion system for 3D image interpretation is often a difficult task that is emphasized by the non understandability of the parameters by the end-users. Moreover, such fusion systems are complex because they involve a complete information treatment chain (from the information extraction to the decision). The sub-parts of the system concern also different scientific areas which add some additional difficulties. Some parameters cannot be easily set empirically and their adjustments are made by trials and errors. This paper studies an optimization of a generalized Choquet Integral parameters by means of genetic algorithms. Fuzzy measures are first learnt thanks to the reference data given by experts and then the best importance coefficients are searched around the initial ones. The approach is illustrated on a cooperative fusion system based on Choquet Integral and devoted to 3D image interpretation.

Keywords: Cooperative fusion system, complex system, genetic algorithms, performance evaluation.

1 INTRODUCTION

With the growth and availability of 3D image devices, more and more it is necessary a quick and correct interpretation for this kind of data. In order to facilitate this work, cooperative fusion systems devoted to image interpretation help experts in the difficult task of image interpretation, which generally consists in detecting typical regions within the images. A synoptic of such fusion system is presented on Figure 1.

The input of the fusion system is the original images and the system tries to build a cartography. These systems are composed of several subparts. The first sub-system concerns the extraction of a piece of pertinent information from the original image. Several image processing techniques could be used to characterize the different sought-after regions. Then the extracted information must be represented into a common and commensurable space in order to be aggregated in the following sub-system. Finally, the output is expressed in an understandable space for the end-user. This step is achieved by the representation sub-systems. Such systems generally imply excessive computation time. They also have many parameters that are not easy to use and to adjust by the end-users. The parameter setting and attributes selection are strongly necessary to obtain relevant results. Unfortunately, the end-users of this kind of fusion system are not specialists in computer sciences and they need help to interact with the system. This is reinforced by the fact that an optimized adjustment obtained for a given data is not compulsory the best one for other data. Fusion systems that propose such functionalities are called elucidative fusion system in the literature [11].

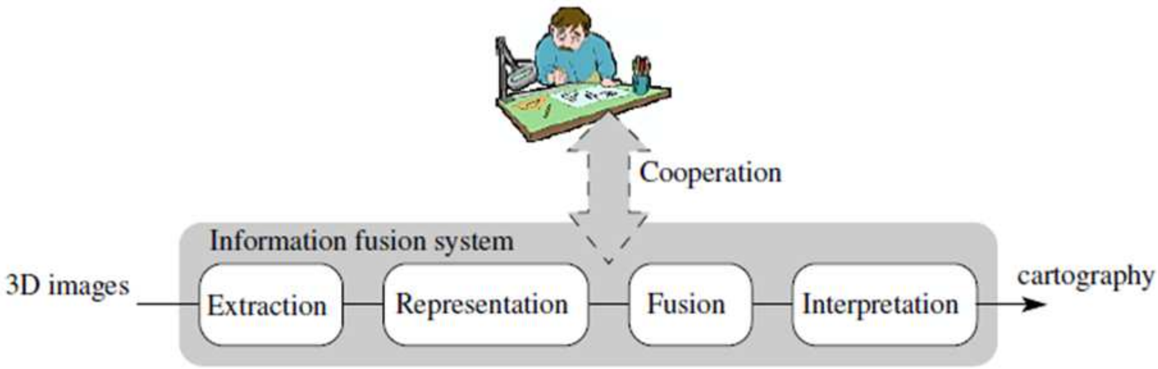

Figure 1: Synoptic of a fusion system for 3D image interpretation

The work presented in this paper belongs to this context. Generally, the first step in the design of a fusion system consists in finding the better way to represent the available information and to aggregate them with an adapted function. The objective is to take into account the different characteristics of the information (availability, certainty, completeness, etc.). Many mathematical tools have been proposed and adapted to answer such issues.

Nowadays, two main difficulties remain important concerning the use of such information fusion systems. The first one concerns their performance evaluation. Indeed, the quality notion is hard to define and currently only a global evaluation of the fused results is achieved. The second difficulty concerns the loop-back on the system to improve its performance. What is the impact of the parameters on the results? Which one must be adjusted and how? Is it necessary to add new input information? These are some samples of occurring situations for which the end-users need help.

This work focuses on parameter optimization to the Choquet Integral existing in the fusion sub-system. These parameters must not violate some fuzzy constraints and the fine adjustment of them needs some loop-back. In this context, the paper shows that the application of genetic algorithms is an interesting way to locally optimize parameters that should have some impact on the fused result.

The paper is organized as following: section 2 presents the concerned fusion system and its end user interaction context. Section 3 presents the genetic algorithm proposed in this work. Section 4 demonstrates the results obtained with the proposed approach on the application. Finally, section 5 is related to conclusions and perspectives.

2 THE FUZZY MEASURE OPTIMIZATION PROBLEM

In the general context of supervised systems, interaction with the end-users is a key issue. These systems are generally complex because they involve several scientific domains, they have numerous parameters and they are composed of several consecutive stages. In [1], a fusion system for 3D image interpretation was presented. Based on Choquet Integral, it allows to build global similarity maps for the detection of different regions of interest. A schematic view of the system is given in Figure 2. In this synoptic, the processing is divided into four main stages. First, different image characteristic measurements based on image processing techniques have been implemented to acquire pertinent information on the sought-after regions. The main family measures are based on local organization (gradient analysis) and texture measurement (co-occurrence matrix). The representation step consists in building similarity maps for each attribute and for each region. All the information is thus expressed in a common and commensurable space. Then, the aggregation sub-parts are made by a Discrete Choquet integral. Fuzzy measures that characterize the attribute importance are learnt for each region thanks to a learning set of points given by experts.

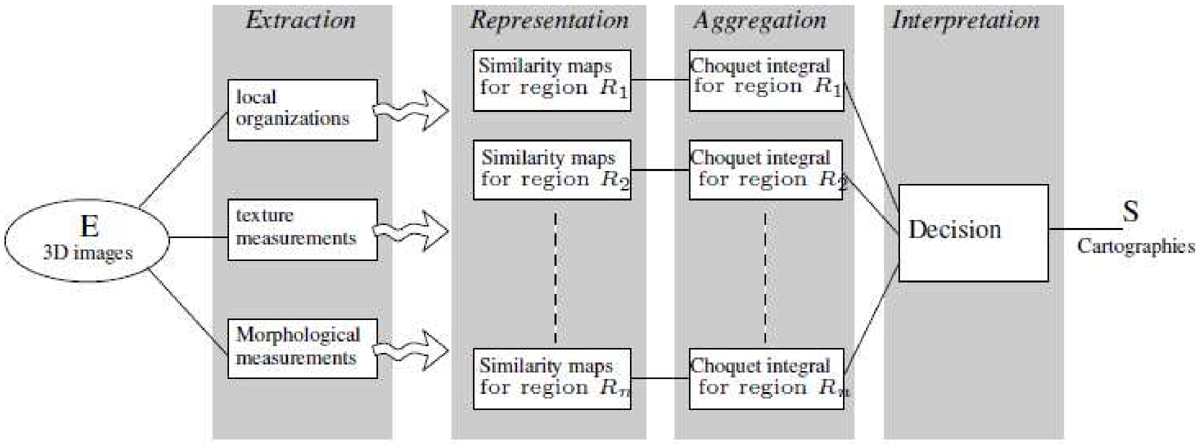

Figure 2 - Schematic view of the fusion system

This system has shown its importance for different 3D image applications but the main difficulty remains on its setting up. Indeed, there is first the choice of which attributes have to be extracted, then all the stages involve numerous parameters not easy to adjust. Given the difficult to proceed on the system knowing only the global detection, a local evaluation of each sub-parts has been achieved in order to better understand the system behavior [2]. It allows to guide the users on where acting on the system to improve the concerned sub-parts and consequently the global detection. Nevertheless, the way the parameters have to be adapted is also strongly difficult to correlate with the output result. An expert on image processing or aggregation tools can adjust many of them empirically when he knows well the meaning and the effect of the parameters. But it turns a difficult task due to the complexity of the system and to its numerous sub-parts that interacts each other. In [3], genetic algorithm was used to optimize the extraction sub-parts of the system. It has permitted to find some set of parameters that would not be naturally given by an expert (i.e. a specific window size more adapted to the scale and the orientation of a given region).

This paper focuses on the aggregation tool parameters. A generalized Choquet Integral [4] is applied for each region of interest to build a global similarity map. The obtained similarity map contain, for each voxel, a global degree representing the similarity of the voxel to the region. This similarity is computed thanks to the information coming from the attributes. The different attribute values are combined using a fuzzy measure that represents the importance of each attribute (and a subset of attributes). This fuzzy measure is learnt [1, 5] from a set of reference data given by the experts on which a relative entropy is computed. By this supervised way, the obtained fuzzy measure represents the knowledge transmitted by the experts through the reference set.

The unique way for modifying these parameters is to add some new reference points that can improve the signature of the regions. Nevertheless, the learning process of the initial fuzzy measure is based on the comparison by the relative entropy operator of two probability density functions build from the reference samples and the input similarity maps [1]. Even if this learning process allows to represent well the expert knowledge, it is liable to the noise coming from the data acquisition. Before asking experts to add some references, the work presented in this paper focuses on an optimization process of the fuzzy measures around their initial values to keep the same meaning (behavior) as the expert one.

The learning of fuzzy measures has been largely studied in the past and the proposed methods are mainly characterized by their complicate computations. Optimization approaches have thus been implemented to answer this problem. In [8], Lee and al. have proposed since 1995 an identification of λ-fuzzy measure by genetic algorithms and they pointed out the usability of the proposed approach and its simple computations. Other techniques have also been used like particle swarm optimization [9] in a supervised context (learning from data) or also self-organizing maps [7] in an unsupervised context. In [10], [14] and more recently in [6], genetic algorithms were efficiently used for determining such nonadditive set functions with the advantage to have a weak risk to fall into a local optimum of the objective function.

3 GENETIC ALGORITHMS FOR CHOQUET INTEGRAL PARAMETRIZATION

3.1 Genetic Algorithms

The genetic algorithm (GA) is a heuristic applied to find optimal or sub-optimal solutions in many complex optimization problems. GA is considered a nature inspired method, belonging to a class of evolutionary algorithms, and has been popularized by [12]. It is inspired in the Darwin evolution theory and it is constituted of a population of individuals that evolve along the generations reaching the fittest individuals. This evolution process can be described as an optimization process.

In GA, the candidate solutions of the problem are encoded as genes in a chromosome. Each gene represents a variable of the solution and a population composed of chromosomes (or individuals) evolves by the following genetic operators: selection, crossover and mutation. Each individual is evaluated by a fitness function (objective function of the optimization problem) and the fittest ones present higher chances to be selected to reproduction. In the next stage they are submitted to crossover and mutation by respectively, exchanging genes with other individuals and suffering some random change in the current genes. So, the population is updated by replacing all parents by their offspring. The evolution converges after a fixed number of generations or other stop criteria.

3.2 Parameter optimization for the Choquet Integral

A generalized Choquet Integral [4] is applied for each region of interest to build a global similarity map. This similarity is computed from the attributes information. Different attribute values are combined using a fuzzy measure that represents the importance of each attribute.

Providing consistent fuzzy measure values is not easy since they have to be subjectively determined by the experts. Figure 3 shows the place of the fuzzy measure optimization process in the aggregation stage of the fusion system.

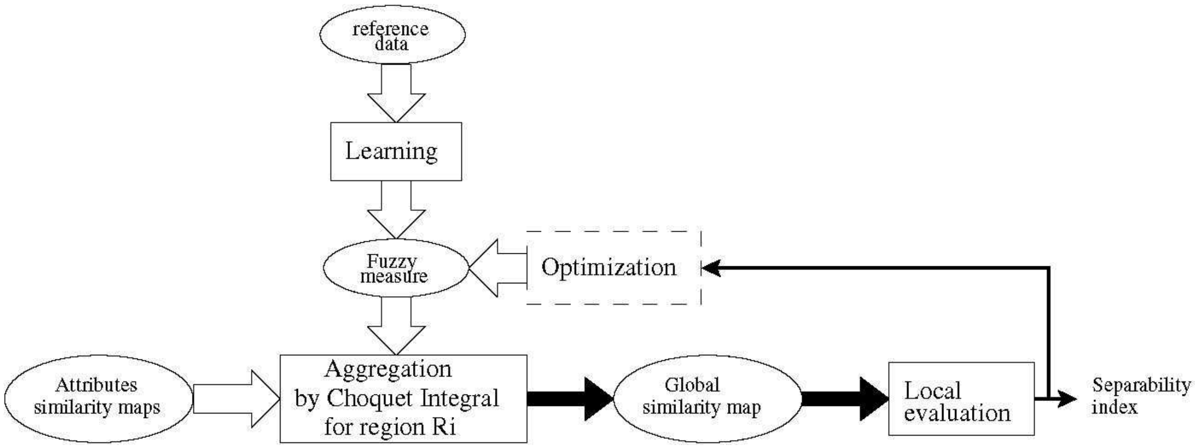

Figure 3 – Fuzzy measure optimization

The local evaluation of the aggregation sub-parts is done by a separability index *S*, varying between [0,1]. The separability index *S* is based on Earth Move Distance (EMD), and is an indicator of how much a region *r* under study could be segmented in the aggregation phase, as described in [2]. The separability index is used as objective function and must be maximized. It is also recalled that a normalized fuzzy measure on *X* is a set function, $P(X) \rightarrow [0,1]$, which satisfies the following conditions:

- $\mu(0) = 0$ and $\mu(X) = 1$
- $A \subseteq B \Rightarrow \mu(A) \leq \mu(B)$ (monotonicity)

(1)

In the case where three inputs (N=3) are used for the Choquet Integral during the aggregation phase, it totalizes eight parameters to be determined (2^N). These parameters μ must follow the constraints expressed in Table 1. The parameters $\mu(0)=0$ and $\mu(N)=1$ are fixed to provide a normalized fuzzy measure, therefore, only six parameters need to be determined.

To encode this solution, the chromosome for the GA proposed here is represented as a set of six genes *M={m(1), m(2),…,m(6)}* with a real value representation. The initial population is created randomly, with values limited between 0 and 1.

Table 1: Genes and parameter constraints for the Choquet Integral

Gene	Parameter	Constraint
M(1)	$\mu(a1)$	$\leq \mu(a1,a2)$ and $\leq \mu(a1,a3)$ and $\leq \mu(N)$
M(2)	$\mu(a2)$	$\leq \mu(a1,a2)$ and $\leq \mu(a1,a3)$ and $\leq \mu(N)$
M(3)	$\mu(a1,a2)$	$\leq \mu(N)$
M(4)	$\mu(a3)$	$\leq \mu(a1,a3)$ and $\leq \mu(a2,a3)$ and $\leq \mu(N)$
M(5)	$\mu(a1,a3)$	$\leq \mu(N)$
M(6)	$\mu(a2,a3)$	$\leq \mu(N)$

During the evolution process, some individuals may violate one of the parameters constraints displayed on table 1 and are called called infeasible solutions. An infeasible solution is a solution that does not respects the monotonicity condition (1) and it cannot be interpreted as a fuzzy measure, and the Choquet integral cannot be computed for such a solution. Thus, those infeasible solutions are discarded, and new random individuals not duplicated are generated on their places.

The fitness values of the candidate solutions is computed by eq (2) where S_r is the separability index and *r={r=1,r=2,r=3}* represent the region number.

$$f = S_r(M) \tag{2}$$

Only the feasible individuals are submitted to the interpretation phase, which uses the Choquet Integral to determine the separability index S_r. In a previous experiment, the infeasible individuals were not discarded, but computed in the fitness function as a penalty value. This approach is no longer used, as there is no difficulty to generate a random feasible individual.

The selection of individuals for reproduction is done by the fitness-proportional *roulette wheel* method [13]. Other operators employed are two-point crossover and a simple mutation strategy with 1/3 from the individual genes selected randomly to mutate.

In order to insert some orientation in the GA evolutionary process and provide cooperation between the system and the end users specialists, those end-users have the option to insert parameters in the system. These parameters *Me={me(1), me(2),…,me(6)}* , are represented as one individual, which is kept in the population as an elite individual, and is never removed during the GA execution.

4 EXPERIMENTS AND RESULTS

The 3D image presented in Figure 3 provides a controlled data for the experiments. It is a gray scale image, with 8 bits encoded and composed of three textured regions. The first region, denoted R1, is a region with low intensity variance. The second region, denoted R2, is a region with high intensity variance compared to R1. The third region, denoted R3, is composed of a succession of two textures that form a kind of oriented region.

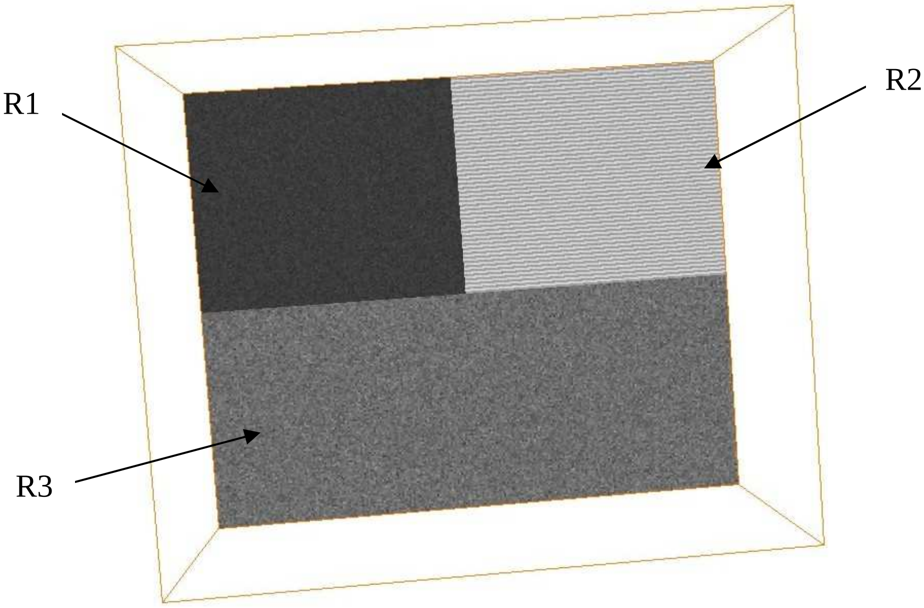

Figure 4 – Artificial image generated for the experiments.

As described in section 3.2, the initial expert based parameters *Me* for Choquet Integral are inserted as an elite individual on the population. In order to understand and validate this expert choice, the same experiment was performed as a global search with the values for each gene *m*(i) limited between 0 and 1. A local search based on the expert parameters for Choquet Integral, was also performed with the values for each gene limited to a neighborhood between $me(i)-0.1>m(i)>me(i)+0.1$.

The GA experiment was performed with the execution parameters displayed in Table 2. To ensure the GA stability, both experiments were executed 10 times. The maximum population was limited to 40 individuals, and to better explore the search space, the population was initialized with 80 individuals. The separability indexes based on EMD distance are used for the fitness functions. Table 3 summarizes the separability index results by means of the average and standard deviation (in parenthesis) for each region, as well as the separability index resulted from the parameter selection by the expert (without optimization).

Table 2: GA parameters.

Parameter	Value
Initial population size	80
Maximum population size	40
Crossover rate	0.60
Mutation rate	0.05
Number of generations	20
Distance	EMD

Table 3: Separability index results

	Search limit	*R1*	*R2*	*R3*
$S_r(M)$	Expert Parameters	0.4574	0.3577	0.4395
	Local	0.4803 (0.0012)	0.3902 (0.0036)	0.4691 (0.0012)
	Global	**0.5127 (0.0010)**	**0.4411 (0.0021)**	**0.4973 (0.0053)**

According to the results presented in Table 3, the global search demonstrates higher separability values if compared with the local search and expert parameters'choice in all regions. The ten best individuals of the global search demonstrated parameter values *Mg* close to the ones set by the expert, *me(i)-0.2>mg(i)>me(i)+0.2*. The local search also obtained greater values of S_r than the expert parameters results. Nevertheless, as explained in section 2, this fuzzy system is based on expert cooperation, and the separability index S_r is not the definitive result, but an indicator that the processing is evolving fine, as the aggregation phase output must be submitted to the interpretation phase. In fact, the expert parameter has greater priority in the entire process, and in this work, the local search, together with the global search, demonstrated to be a helpful tool to provide clues and feedback to adjust the expert parameters.

The impact of the fuzzy measures optimization on the fusion system is studied by the detection rate computed on the final output of the fusion system. The final decision on the matching of a voxel to a region is achieved by the interpretation stage thanks to a severity degree. This value is used as a threshold on the similarities obtained by the Choquet Integral and the voxels are classified to a region that has the similarity superior than the threshold (severity degree).

Figure 5 presents the global rates according to the severity degree for the three cases: without optimization, with local optimization and with global optimization. Analysis of these plots leads to three interesting comments. First, for low values of the severity degree (below 0.2), there is less ambiguity between the region when the optimized parameters are used in the Choquet Integral. The risk when the severity is low is to have many miss-classified voxels and the plot shows that the new parameters brought more robustness on this hand. Then, for a severity degree between 0.3 and 0.6, the rates are quite similar. Finally, for severity degree superior than 0.6, the rates have also largely improved. It means that when the severity degree is increased, (that is to say when we ask that voxels must have a strong similarity with the regions), then there is much more voxels that are well classified (with certitude). For example, there is 5% of voxel (621 000 voxels) well-classified when the severity is set to 1.0 (compared to 0.2% without optimization). The global behavior of the system is thus improved by the optimization.

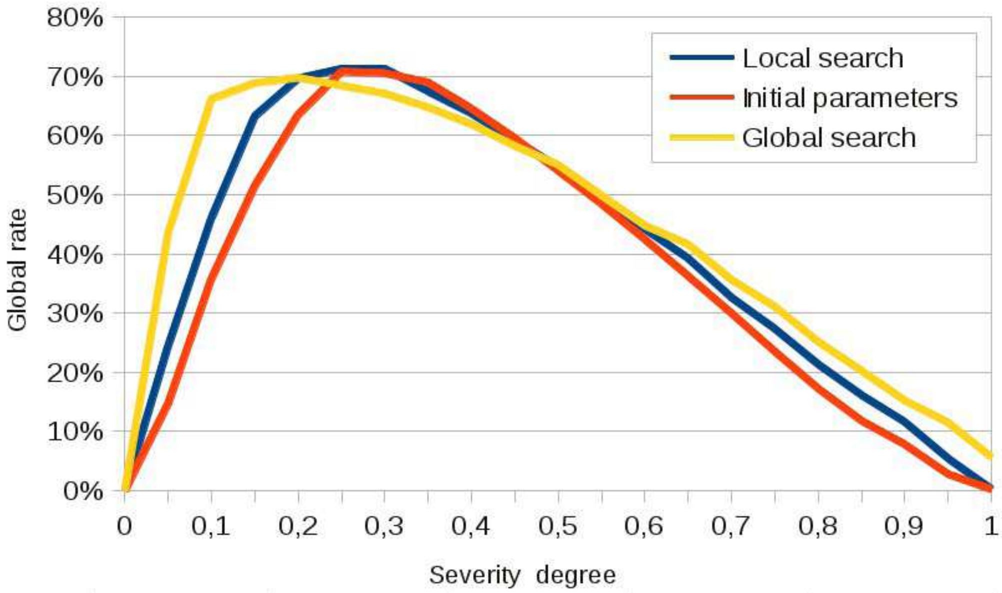

Figure 5 – Global Rates versus Severity Degree

5 CONCLUSIONS

Fusion systems that are supervised by experts require efficient tools that facilitate interaction. The complexity of such systems mainly lies in the different scientific domain involved in the processing chain. From image processing to decision support, the information must be represented and aggregated using adequate techniques. The sub-parts that compose such systems have numerous parameters that need to be adjusted to fit new data or different kind of regions of interest. Some of them can be set empirically by experimented end-user but other ones are learnt from reference sets. Learning is an interesting way to represent expert knowledge but this approach is strongly dependent on the data quality. In image based application, there is always noise coming from the acquisition which is transformed under uncertainty on the data. Parameters learnt on such data are not necessary the best one.

This paper has dealt with this problem for fuzzy measures used by Choquet Integral to aggregate similarity maps. The fuzzy measures are optimized using genetic algorithms to maximize the separability indexes. Two experiments were executed: a global search and a local search. The last one was performed around the initial parameters selected by the expert. The experiments showed that the global search reached the highest separability index in all regions. The new parameters found brought more robustness on the obtained detections thanks to a better separability of the regions. There is less ambiguity between the regions which facilitate the final decision. The behavior is improved for the different values of the severity degree that condition the output. Works are currently in progress to reinforce the approach attractiveness when more inputs are used in the aggregation stage of the fusion system.

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