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Image enhancement through intelligent localized fusion operators in the automated visual inspection of highly reflective surfaces

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Abstract

The selection of a suitable illumination subsystem is seldom practicable in the automated visual inspection of highly reflective surfaces. The paper presents an algorithmical approach in the form of a framework for enhancing images of objects with such surfaces. This framework is based on the application of so-called Intelligent Localized Fusion Operators (ILFOs), whose formalization is herein undertaken for the first time. Furthermore the guidelines for its implementation are given and different aspects of the resulting pre-processing system are systematically analyzed. The framework successfully performs in the automated visual inspection of different objects presenting highly reflective surfaces, namely headlamp reflectors, plastic bundled packages, and electric bulbs.

Keywords: Fuzzy integral; Fuzzy measures; Image enhancement; Image processing

1. Introduction

The automated visual inspection of objects with highly reflective surfaces results extremely complex due to the presence of some areas in the acquired images, where the camera detector is saturated. These areas are known as highlights. Though this problem can be tackled by applying a suitable lighting system, this solution is not trivial and seldom practicable for such objects. In this context the application of a pre-processing system for filtering the highlights becomes extremely helpful.

Following the seminal paper of Burt and Kolczinsky [1] image fusion has been applied for image enhancement in different applications. In [1] an image pyramid is used in order to fuse a multi-focal image set through a weighted sum operator. On the other hand, the active consideration of the illumination conditions in the image acquisition process in order to obtain a well-conditioned input image was taken into consideration in [2] for the first time. As an extension of these two works, some research groups [3–5] apply image fusion on a multi-dimensional image set resulting from different illumination conditions in order to enhance it.

The framework proposed in [3] is based on a model-based approach for the evaluation of the fused image energy [6]. Different images taken under varying illumination conditions are fused within a probabilistic Bayesian framework, where the employed fusion operator can be modeled as a weighted sum. The second approach [4] applies a so-called comparametric processing of an image set taken under different exposure times. The used comparametric equations are related to the fields of photometry and radiometry. They are applied in order to increase the signal-to-noise ratio of the output image. Thus, the image fusion results from the application of diverse non-linear functions.

In the framework presented in [5] a multi-dimensional set of images taken under different illumination conditions

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are fused with a so-called Intelligent Localized Fusion Operator (ILFO), which is a further development of the fuzzy integral [7] within a theoretical framework denoted as soft data fusion [8,9]. This theoretical framework focus its attention on the role of the operator binding the data from the different information sources in multi-sensory systems. In this context, the fuzzy integral, which presents a non-linear function for the fusion of information, plays a principal role because it generalizes the more common fusion operators. Thus it subsumes the weighted sum approach employed in [1,3]. In contrast to the other non-linear methodology proposed in [4], ILFOs improve the interpretability of the fusion operator because of its relationship to the field of Fuzzy Computing. The framework presented in [5] attains for the first time the filtering of highlights as a pre-processing task in automated visual inspection, whereas the frameworks in [3,4] attain the general image enhancement of the input images.

The here presented paper furthers the framework based on ILFOs [5]. The formalization and the automation of different aspects of the framework is undertaken herein for the first time. The formalization succeeds by taking the Theory of Fuzzy Sets [10] and the Pattern Recognition approach presented by Watanabe [11] into account. Moreover, the novel application of peak dynamic analysis [12] for the automation of the process allows the framework to attain the results without heuristic parameterization. This fact constitutes a clear advance with respect to the framework presented in [5]. Although some results could look the same as those obtained in [5], the application of genetic algorithms [13] is newly done herein. In [5] the best results were obtained through the manual modification of the parameters deliver by the genetic algorithms. No manual adaptation is undertaken herein. Furthermore, the following properties of the framework are analyzed herein: automation, best parameterization and convergence of GAs, execution time, generalization capability, and quantitative evaluation of the resulting images' quality. The employment of Interactive genetic algorithms [14] is presented herein for the first time as an alternative to GAs.

The paper is organized as follows. Section 2 gives an overview of the theoretical background on the fuzzy integral, including the more general framework of soft data fusion and some considerations on the application of the fuzzy integral for image fusion. The formalization of ILFOs is attained in Section 3. The pre-processing framework, which is based on the application of an ILFO for highlights filtering is presented in Section 4. The results obtained by applying this framework in different automated inspection systems can be found in Section 5, where the inspection of automotive headlamp reflectors, plastic bundled objects, and electric bulbs is described. The first application is used in order to undertake the systematic analysis of the framework. Finally the conclusions are given in Section 6.

2. Theoretical background

2.1. Soft data fusion and the fuzzy integral

The theoretical framework of soft data fusion [8,9] relate different fusion operators by taking the flexibility of the operation result into account. In this sense traditionally used fusion operators can be considered as hard. Fuzzy fusion operators were established as generalizations of classical ones. This mathematical generalization can be considered as a softening process of the operator, which improves the mentioned flexibility.

The consequence of the evolution of fusion operators from harder to softer ones is shown in the following paragraph. In classical operators the fusion result exclusively depends on the value being operated on. For instance the result of the sum operator just depends on the summands and thus $1.9 + 3.1$ is always computed to 5, different from values "close to 5" like 4.9. The result of such a fusion operation through the application of a softer operator, i.e. a weighted sum, an Ordered Weighted Averaging [15], or a Fuzzy Integral [7], differs from this hard one. This difference is based on the inclusion of an increasing number of freedom degrees in the operators as shown in [9]. While in weighted operators the weight of the information sources is established upon its index, weighted order operators establish the weight upon the ranking of the information sources. This difference improves the performance of the operation w.r.t. compatibility, partial aggregation, and reinforcement [16].

Fuzzy integrals further increase the flexibility of the operator by taking the fusing values, the *a priori* importance of the fusing sources, and their ranking into consideration in the fusion result. This can be observed on hand of the mathematical expression of the Choquet Fuzzy Integral (CFI):

$$\mathscr{C}_\mu[h_1(x_1),\ldots,h_n(x_n)] = \sum_{i=1}^{n} h_{(i)}(x_i)\cdot[\mu(A_{(i)}) - \mu(A_{(i-1)})] \tag{1}$$

where $\mu(A_{(i)}) = \mu(\{x_{(1)},\ldots,x_{(i)}\})$ denote the coefficients of so-called fuzzy measures $\boldsymbol{\mu}$ and $h_i(x_i)$ the fuzzified information sources. The enclosed sub-index states for the ranking result, i.e $x_{(1)} \geqslant x_{(2)} \geqslant \cdots \geqslant x_{(i)}$. This operation determines the coefficients of the fuzzy measures employed in the integration. The reader is referred to [9,17] for a deeper description of this operator.

The fuzzy measure coefficients are used for quantifying the *a priori* importance of the information sources. Fuzzy measures $\boldsymbol{\mu}$ are functions on the power set of information sources $\mathscr{P}(X)$, whose coefficients are defined in the interval $[0,1]$ and fulfill the so-called monotonicity condition:

$$A_j \subset A_k \to \mu(A_j) \leqslant \mu(A_k) \quad \forall A_j,\ A_k \in \mathscr{P}(X) \tag{2}$$

The fuzzy measure coefficients of the subsets with cardinality one are denoted as fuzzy densities $\mu(\{x_i\}) = \mu_i$. They

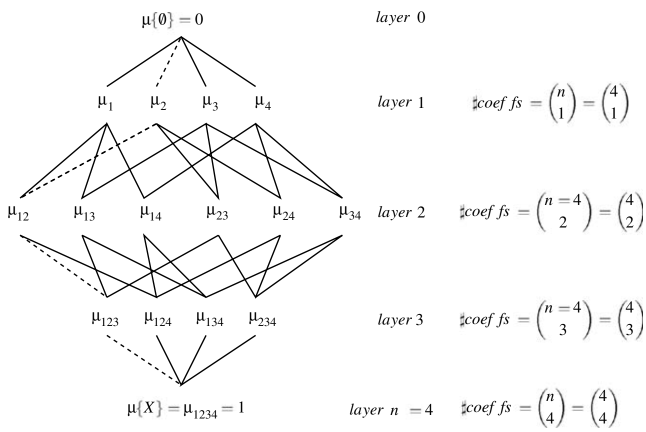

Fig. 1. Lattice structure of a fuzzy measure up to [18]. The data structure constitutes a graph with unidirectional links from $\mu\{\emptyset\}$ to $\mu\{X\}$. The sorting operation of the fuzzy integral, Eq. (1), fixes up the path for the selection of the fuzzy measure coefficients. For instance a dotted line marks the path for the coefficients selected if $x_2 > x_1 > x_3 > x_4$, since then $x_{(1)} = x_2$, $x_{(2)} = x_1$, $x_{(3)} = x_3$, and $x_{(4)} = x_4$.

quantify the importance of the individual sources. The remaining coefficients $\mu(\{x_i,\ldots,x_j\}) = \mu_{i\ldots j}$ quantify the importance of the coalitions among them [17].

2.2. The fuzzy integral in image processing

The complexity of fuzzy measures makes a lattice structure suitable for its implementation [18]. Such a graph structure (see Fig. 1) presents $n+1$ layers, where n is the number of information sources, connected by unidirectional links. The nodes of the graph are occupied by the coefficients corresponding to each of the subsets of $\mathscr{P}(X)$. Each layer is occupied by the $\binom{n}{i}$ coefficients that correspond to the subsets with the same cardinality. The links connect the subsets among the different layers that satisfy the monotonicity condition (2) of the fuzzy measure. The employment of look-up tables constitutes an alternative to this data structure which can help optimizing the computational cost of the fuzzy integral operator.

An algorithm of the fuzzy integral for image fusion is presented (see Algorithm 1). The algorithm makes use of the lattice structure formerly presented. Thus, the fuzzy integral is iteratively computed by following the links in the lattice. The used T- and S-norms are defined by the type of fuzzy integral employed [19]. As it can be observed, the fuzzy integral is computed on each pixel of the multi-sensory input image in order to fuse the n image channels into a single one.

3. Intelligent localized fusion operators

Operators for soft data fusion can achieve a higher degree of softness (see Section 2.1) in Image Processing by defining local application domains of the weighting schemes. This is attained within the paradigm denoted as Intelligent Localized Fusion (ILF) [20].

Algorithm 1. Iterative algorithm for image fusion through the fuzzy integral. The algorithm makes use of the lattice structure of fuzzy measures (see Fig. 1).

construct a fuzzy measure FM
for all pixels P in multi-channel image **do**
  $FI \leftarrow 0$
  current node $\leftarrow \mu\{\emptyset\}$
  $\mu_{current} \leftarrow 0$
  sort pixel channels
  for all element CH in sorted sequence **do**
    $\mu_{prior} \leftarrow \mu_{current}$
    follow link in lattice corresponding to the current element
    $\mu_{current} \leftarrow$ coefficient in current node
    if Choquet Integral **then**
      $\mu_{current} \leftarrow \mu_{current} - \mu_{prior}$
    end if
    $TR \leftarrow Tnorm(CH, \mu_{current})$
    $FI \leftarrow Snorm(FI, TR)$
  end for
  $P \leftarrow FI$
end for

Usually the fuzzy measure coefficients are defined by taking the image as a unit (see Section 2.2). In contrast with this fact the used fuzzy measure is said to be "localized" in the ILF paradigm. A "localized" fuzzy measure $\boldsymbol{\mu}$ is defined as a set of fuzzy measures $\boldsymbol{\mu}^j$. Each element of this set operates on a particular area j of the image domain. The mapping between $\boldsymbol{\mu}^j$ and the image sub-domain where it operates is defined through a label image. A fuzzy integral operated with respect to such locally defined fuzzy measures becomes a so-called Intelligent Localized Fusion Operator, ILFO. It is noteworthy to take into consideration how ILFOs are mathematically defined and how they can be implemented in engineering systems. This is attained in the following subsections.

3.1. ILFOs' mathematical foundations

The image space X is partitioned by the label image in different subspaces X^j, where different fuzzy measures $\boldsymbol{\mu}^j$ are defined. A mapping is then established between j and the gray-level of the labels g_j.

The definition of the fuzzy measures $\boldsymbol{\mu}^j$ attains the characterization of different importance relationships among the image channels in the corresponding subspaces. The image space is partitioned based on a process of feature analysis. The goal of this feature analysis procedure is the determination and extraction of a set of features, whereby the importance of the information channels can be established. Thence the label image codifies the spatial distribution of

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the analyzed features over the different channels of the input image.

The generation of the label image can be formalized as follows. For the sake of simplicity the description is made for a two channel image (x_i, $i = 1,2$). Being the image space $X = \{X_1,X_2\} \rightarrow G^2$, where $g \in [0, 255]$ for 8-bit grayvalue images, a feature extraction procedure is applied on each channel X_i. Thus a feature (or a group of them) *a priori* characterizing the importance for the fusion operation is firstly extracted, what can be expressed as $X \rightarrow F$. Thence the application of a threshold θ_i over the resulting feature maps leads to the definition of the following sets:

$$\begin{aligned} F_1 \cap F_2 &= \{x/\text{both channels are important for the fusion}\} \\ F_i &= \{x/\text{channel } i \text{ is important for the fusion}\} \\ \overline{F}_1 \cup \overline{F}_2 &= \{x/\text{no channel is important for the fusion}\} \end{aligned} \tag{3}$$

where θ_i sets up the difference between *important* and *not important* on channel i.

The resulting sets can be related to the different levels of the fuzzy measure defined in the image space (see Fig. 2). Hence the intersection $F_1 \cap F_2$ is related to the coefficient in the level 2, namely $\mu(A_1 \cup A_2)$, the sets F_i are related to $\mu(A_i)$, and the union of the complements to $\mu(\emptyset)$. If the goal to be achieved by partitioning the image space is the increment of the flexibility of the fuzzy integral, the monotonicity of the fuzzy measure has to be broken. This cannot be achieved with just one measurable space as stated by Eq. (2). Therefore the image space is divided in three different subspaces $\mathscr{C}^j$ through the mapping $X \rightarrow F \rightarrow \mathscr{C}^j\ \forall j = 1,2,3$, where three different fuzzy measures $\boldsymbol{\mu}^j$ can be defined. Thus these fuzzy measures can break the monotonicity condition by presenting $\mu^1_{12} \leqslant \mu^2_1$ and $\mu^1_{12} \leqslant \mu^2_2$.

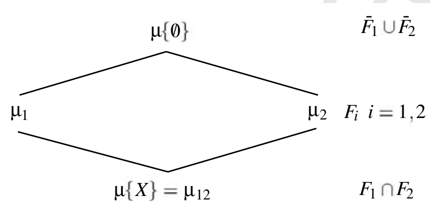

Fig. 2. Relationship among feature sets and levels in the lattice structure of a fuzzy measure which is used for deriving the expression of an ILFO.

The subspaces, where the different fuzzy measures $\boldsymbol{\mu}^j$ are localized, can be defined upon the following classes:

$$\begin{aligned} &\mathscr{C}^1 = \{F_1 \cap F_2\} && \Rightarrow \boldsymbol{\mu}^1 \\ &\mathscr{C}^2 = \{F_1 - (F_1 \cap F_2), F_2 - (F_1 \cap F_2)\} && \Rightarrow \boldsymbol{\mu}^2 \\ &\mathscr{C}^3 = \{\overline{F}_1 \cup \overline{F}_2\} && \Rightarrow \boldsymbol{\mu}^3 \end{aligned} \tag{4}$$

The set difference of the second class assures the classes to be disjoint, i.e. each point can just belong to one class. The generalization of these definitions for three channels is depicted in Fig. 3. The class definitions for a larger number of classes can be defined in an analogous manner. Here the number of classes m is determined by the number of levels to be singularly considered in order to overcome the monotonicity of the fuzzy measure (see Fig. 2), being $m = n + 1$ and n the number of information sources.

The former definitions can be also generalized by applying the Fuzzy Set Theory [10]. This is attained by applying a tolerance factor ε over the threshold θ (see Fig. 4). In this case, the classes $\mathscr{C}^j$ become fuzzy classes. Moreover the points of the label image present so many membership degrees as classes are defined, therefore becoming a fuzzy label image. Hence, each point presents a membership degree for each of the classes that will be denoted as ζ_j, $\forall j = 1,\ldots,m$. The result of the ILFO is the linear combination of the fuzzy integrals for each class:

$$\text{ILFO}[h_1(x_1),\ldots,h_n(x_n)] = \zeta_1 \mathscr{F}_{\mu^1} + \cdots + \zeta_m \mathscr{F}_{\mu^m} \tag{5}$$

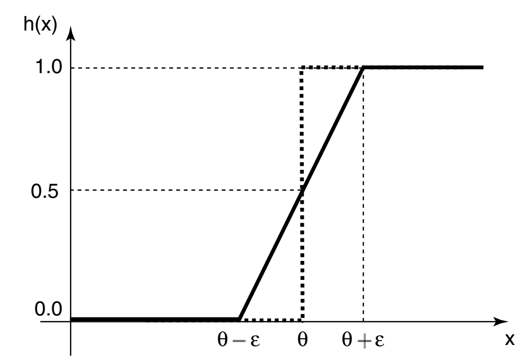

Fig. 4. Tolerance parameter ε for the fuzzification of the feature images in an ILFO with a fuzzy label image. The parameter turns the step function centered on θ (dotted line), which would have been used as threshold for the generation of a crisp label image, into a ramp-shaped fuzzy membership function (continuous line).

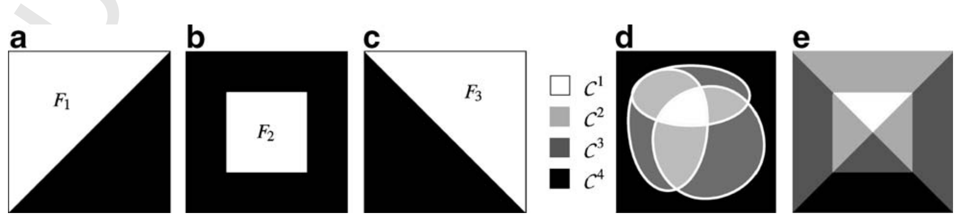

Fig. 3. Set diagram for the generation of a label image to be used in an ILFO, exemplary shown for three input channels. The process is based on the following set and class definitions: $F_i = \{x_i/\text{presents computed feature}\}\ \forall i = 1,2,3$; $\mathscr{C}^1 = \{F_1 \cap F_2 \cap F_3\}$; $\mathscr{C}^2 = \{(F_1 \cap F_2) - \mathscr{C}^1, (F_1 \cap F_3) - \mathscr{C}^1, (F_2 \cap F_3) - \mathscr{C}^1\}$; $\mathscr{C}^3 = \{F_1 - \mathscr{C}^2, F_2 - \mathscr{C}^2, F_3 - \mathscr{C}^2\}$; $\mathscr{C}^4 = \{\overline{F}_1 \cup \overline{F}_2 \cup \overline{F}_3\}$. (a–c) Binary maps resulting from the binarization of the corresponding feature map. (d) Venn diagram of the class definition. (e) Resulting label image.

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where $\mathscr{F}_{\mu^j}$ states for any fuzzy integral (although the CFI equation (1) is herein taken into consideration).

3.2. ILFOs' framework

The following section presents the framework of a generic ILFO. The implementation of an ILFO is composed by three different modules: *LabImGen*, which generates the label image where the fuzzy measures are localized, *FuzMeCo*, which constructs these measures, and *FuzFus*, which implements the expression given in Eq. (5). Since the implementation of the module *FuzMeCo* is application dependent, just the implementation of the label image generation is elucidated in the following paragraphs. The reader is referred to [5] for an extended description of the generic framework.

The block diagram of the module used for the generation of the label image (*LabImGen*), which was formally defined in Section 3.1, is shown in Fig. 5. The different modules are described in the following paragraphs.

Through the *FeatExt* module a particular feature of the image is analyzed and characterized. A numerically expressed feature is extracted from each of the input channels in this feature stage. This feature characterizes the importance of the channel for the fusion result. Examples of such a characterization could be the extraction of a blurring coefficient or of the areas with low luminance.

In the binarization stage, which is implemented through the module denoted as *Binar*, each of the feature distribution maps is binarized with θ_i. The parameter θ_i represents the point up to which the feature evaluated on the channel x_i is considered to be important enough in order to influence the fusion result. Thus the resulting binary maps represent this importance through a binary variable (see Fig. 3a–c). Furthermore this module implements the set definition of F_i as expressed by Eq. (3).

The purpose of the expert system (in the module *ExpSys*) is the computation of the classes for the definition of the different fuzzy measures as stated for instance in Eq. (4). The expert system generates the binary images whose true values indicate whether (and where) the feature is important in the first channel, in the second channel, in the first and second one, and so forth, etc. Afterwards these sets are grouped in the different classes by applying the corresponding logical operators, i.e. AND, OR, and NOT.

The last module *Codif* takes the binary maps of the former module as input. *Codif* generates the label image (see Fig. 3e) by codifying the image points of each class j with a grayvalue g_j. The outgoing label image is used for the computation of the ILFO as already described.

If a fuzzy label image is generated, the module *Binar* is substituted by a fuzzification module that implements the fuzzification of the feature images with the monotonic increasing fuzzy membership function defined by the tolerance value ε (see Fig. 4). The fuzzification module delivers a set of fuzzy images to the expert system. Therefore the rule system (*ExpSys*) becomes a fuzzy rule system. The treatment of the fuzzy images resulting from the fuzzification stage are operated in this case with T-norm, S-norm and fuzzy complement operators [21].

The output of the procedure changes as well in this fuzzy implementation. A set of fuzzy images, which constitute the fuzzy label image, is delivered together with the crisp label image (see Fig. 9 for an exemplary comparison between the two approaches). The membership degrees contained in these fuzzy images will be used as the real coefficients ζ_j in the linear combination expressed in Eq. (5).

4. Application of ILFOs in a framework for highlights filtering

As formerly elucidated, the ILF paradigm can then be applied in the implementation of the pre-processing framework for the automated visual inspection of objects that present highly reflective surfaces [5]. The presence of so-called highlights, areas where the camera detector is saturated, constitute the principal problem in the inspection of these objects. Highlight areas are characterized by the absence of visual information about the object structure. Therefore a set of images, where complementary visual information about the inspected object is contained, is generated in the image acquisition stage. Thence an ILFO is

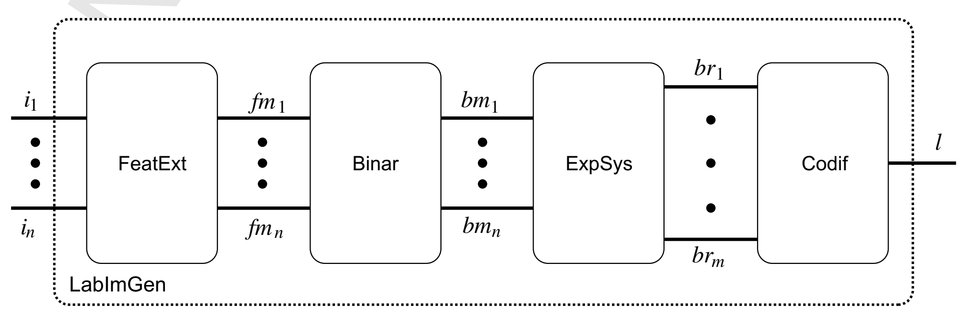

Fig. 5. Block diagram for the generation of a crisp label image in an ILFO. Signals. i_i: Input channels. fm_i: Features maps. bm_i: Binary feature maps. br_i: Binary class maps for different relationships. l: Crisp label image. Modules. *FeatExt*: Feature extraction. *Binar*: Binarization. *ExpSys*: Expert system. *Codif* : Codification.

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applied on the acquired images in order to suppress the highlight areas.

4.1. Image acquisition

Different images of the underlying object are taken with a camera from the same position but with different adjustments and illumination conditions. The image acquisition stage attains the generation of an image set, where the reflections appear in different positions and spatial extensions. The less redundancy among these images, the better result can be attained. Indeed the reflection areas with no structure information cannot be filtered out and therefore the underlying object information cannot be recovered [5].

The image acquisition is not trivial. Since the objects being inspected present highly reflective surfaces, the reflection of the environment on them cannot easily be avoided. Therefore the image acquisition stage should succeed by protecting the camera, the lighting system, and the inspected item from external lights. No other restrictions concerning the surface structure[1] neither the reflection properties have been detected hitherto. Moreover three equal infrared lighting sources have been used in the acquisition of the input image set employed. Thus three images are generated for each item being inspected in the work presented herein. The generation of a larger image set can improve the pre-processing result. Thus more complex acquisition systems, similar to this used in the generation of the Amsterdam Library of Object Images database [22],[2] can be used in order to acquire a less redundant image set.

4.2. Generation of the label image

Once the image set has been generated, the label image for the fusion is computed (*LabImGen*). This is attained through the application on the input images of the modules depicted in Fig. 5 (or its fuzzy implementation). In the filtering of highlights the feature to be extracted characterizes areas with high luminance values. Therefore the grayvalue of the input channels can be used itself as feature. A threshold θ_i is applied on the grayvalue input channels in order to determine the spatial distribution of the highlights on each individual channel x_i.

A procedure used in the generation of the label image is implemented for finding out the threshold θ_i on the feature maps' histograms, whereby the determination of this parameter is automated. The selected algorithm is part of the watershed transformation for the segmentation of multidimensional histograms [12]. It is based on the concept of dynamic of histogram peaks [23], which can be applied on the local extrema of an histogram in order to filter out the less representative ones.

The application of this procedure can be described as follows. First all the local maxima of the inverted histogram are selected (see Fig. 8a). Thence the values of these maxima are sorted in descending order. The dynamic of each local maximum is computed by going through the histogram till the maximum that occupies the next position in the sorted list has been reached. The dynamic value of the outgoing local maximum equals the difference between its value and the minimum value encountered in the way to the next maximum. This operation is repeated for all local maxima in the histogram. The peak with the largest dynamic among those with the larger grayvalue is selected as the threshold θ_i in the application on hand (see the exemplary value in Fig. 8a).

Once the highlights have been found for all the input channels, the label image itself is generated by the corresponding rule system and the posterior codification. The label image codifies then all the different highlights combinations: no highlights, highlight in the first image, highlight in the first and second image, etc.

4.3. Construction of fuzzy measures

A process for the determination of the fuzzy measures is thence undertaken (*FuzMeCo*). The number of different labels in the label image m fixes up how many fuzzy measures have to be constructed. genetic algorithms [13] and Interactive genetic algorithms are employed [14] for this purpose herein.

4.3.1. Genetic algorithms

The characteristic function of Evolutionary Computing is the computation of a solution in non-linear optimization problems [24]. Genetic algorithms have been successfully used for constructing fuzzy measures [25–27]. The fuzzy measure coefficients are first encoded by arrays of real numbers. The general methodology of genetic algorithms with standard operators [13] applies for this problem. The iterative search is driven by a so-called fitness function, which characterizes the optimality of the individual solutions in each step.

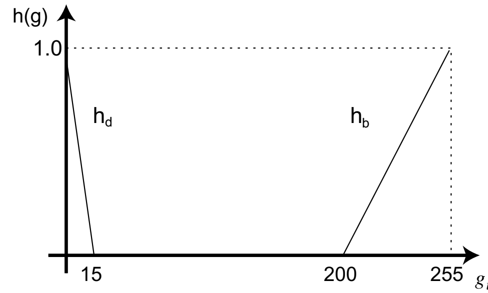
In the here presented application of genetic algorithms three different fitness functions $f_i(x)$, which were proposed in [5], are evaluated. The first function (f_1) presents the following expression:

$$f_1(x) = 0.8\sigma_{\mathrm{g}}^2 + \sum_{i=0}^{N-1}[0.75h_{\mathrm{b}}(g_i) + 0.2h_{\mathrm{d}}(g_i)] \qquad (6)$$

where N states for the number of pixels of the final image, σ_g^2 denotes the variance of the grayvalues, and h_{b} and h_{d}, two fuzzy functions that count the number of pixels with respectively a maximal and minimal grayvalue g_i. The minimization of this function attains the minimization of the number of pixels with extreme grayvalues. The weights of

[1] Obviously the complexity of the 3D structure hinders the visibility of all surfaces of an object, but this is not directly related to the highlights filtering.

[2] The database and some information about the employed acquisition system can be found at http://www.science.uva.nl/~aloi/.



$$h_b(g_i) = \begin{cases} 0 & : \quad 0 \le g_i < 200 \\ \frac{g_i - 200}{55} & : \quad 200 \le g_i \le 255 \end{cases}$$

$$h_d(g_i) = \begin{cases} 1 - \frac{g_i}{15} & : \quad 0 \le g_i < 15 \\ 0 & : \quad 15 \le g_i \le 255 \end{cases}$$

Fig. 6. Fuzzy membership functions used for image quality assessment used in the fitness function (6). The fuzzy membership function $h_b(g_i)/h_d(g_i)$ accounts for the pixels with a low/large grayvalue g_i. The lower/larger the grayvalue, the larger the weighting in the sum.

the three factors were heuristically found. The used triangular fuzzy membership functions, h_b and h_d, are depicted in Fig. 6 beside their mathematical expressions.

The grayvalue distribution of the fused image is driven to present $\bar{g} = 128$ and $\sigma_g = 64$ by applying the second fitness function (f_2), which is mathematically expressed as

$$f_2(x) = \|\bar{g} - 128\| + 2\|\sigma_g - 64\| \tag{7}$$

This expression drives the resulting image to present a "standard" histogram.

The third fitness function (f_3) pursues a minimization of the number of extreme grayvalues in the resulting image, which is characterized by σ_g^2:

$$f_3(x) = \sigma_g^2 \tag{8}$$

4.3.2. Interactive genetic algorithms

Interactive genetic algorithms are employed as an alternative to GAs for the implementation of *FuzMeCo*. The application of interactive genetic algorithms allows evaluating the final result directly by a user, avoiding the complex determination of a fitness function [14].

The fitness computation is substituted by the presentation of the final image result for each individual to the user. Thus the surface of the displaying monitor limits the number of individuals of the population. Populations of between 10 and 20 individuals are used. The user interactively selects the best results. These results are then used for producing the next generation and the process is iteratively repeated. The number of generations is strong limited by the concentration capability of the user. Hence the process takes about half an hour to be completed.

4.4. Fuzzy information fusion

Once the values of the fuzzy measure coefficients have been determined, the fuzzy integral is applied on each pixel of the multi-dimensional image set with respect to the fuzzy measure codified in the label image (*FuzFus*). The result is an image, where the highlight areas have been filtered out.

5. Application results

In the following sections the performance of different systems for the automated visual inspection is analyzed. The systems attain the inspection of different objects that present highly reflective surfaces, namely: automotive headlamp reflectors, consumer goods with plastic bundles, and electric bulbs. The framework formerly described is applied for the pre-processing of the generated images. The results related to the highlights filtering are presented.

5.1. Inspection of headlamp reflectors

The presence of mirror-like surfaces makes the automated visual inspection of automotive headlamp reflectors extremely complex. Therefore the presented pre-processing framework is applied. The images generated are shown in Fig. 7. In the following, different aspects of the system are analyzed in detail.

5.1.1. Generation of the label image trough peak dynamics analysis

The process for the generation of the label image is automated by first applying the analysis of the peak dynamics

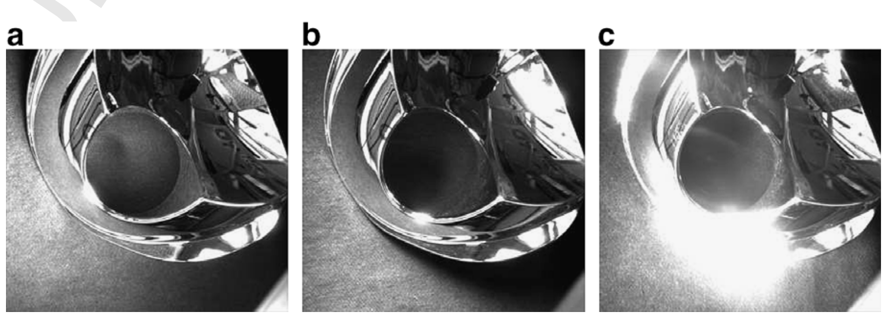


Fig. 7. Input images of the pre-processing stage of a system for the detection of structural faults on automotive headlamp reflectors (item I).

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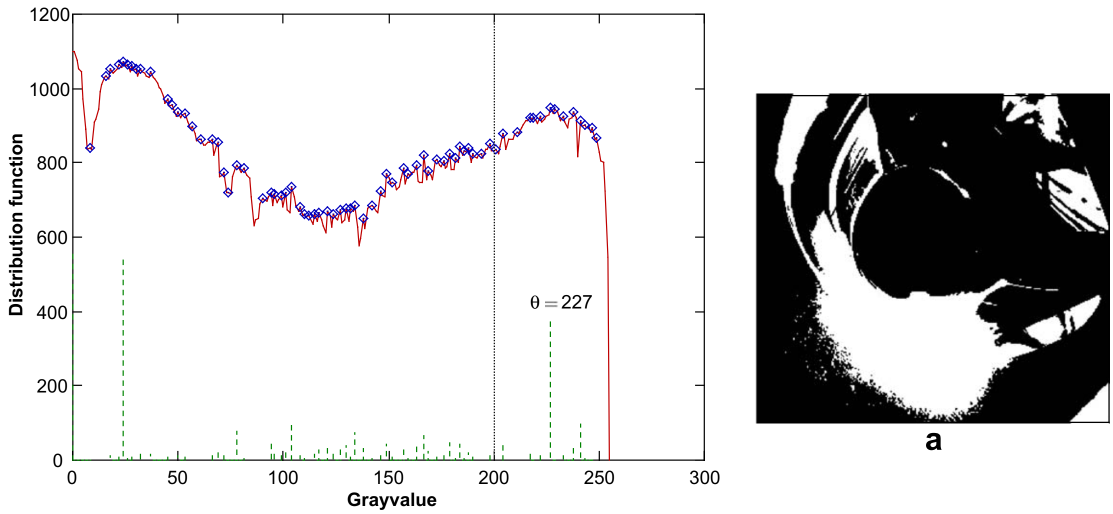

Fig. 8. Exemplary result of the computation of the peak dynamic (green dotted lines) of each local maximum (blue diamonds) on the inverted histogram (red continuous line) of the image shown in 7c. (a) Resulting binarization. (For interpretation of references in colour in this figure legend, the reader is referred to the web version of this article.)

in the image histograms, which delivers the value of the threshold θ_i for each input channel. The result of the peak dynamics analysis and the corresponding binarization are shown in Fig. 8.

The binary images obtained through the automated parametrization, are depicted in Fig. 9a–c. Furthermore the generation of the label image follows the mathematical framework given in Section 3.1 both in its crisp and fuzzy implementations. The resulting label image, and the fuzzy label images for $\varepsilon = 50$ can be seen in Fig. 9d–h.

5.1.2. Construction of the fuzzy measures through IGAs

An interactive genetic algorithm is used for the construction of the fuzzy measures leading to the avoidance of highlights in the fused image. The simulation is undertaken on the images shown in Fig. 7. It pursues the performance evaluation of IGAs by comparing the results with those obtained through the application of GAs, which are presented in Section 5.1.3. The obtained results are shown in Fig. 10.

The interactive genetic algorithm strategy is tested with different parameterizations and different types of fuzzy

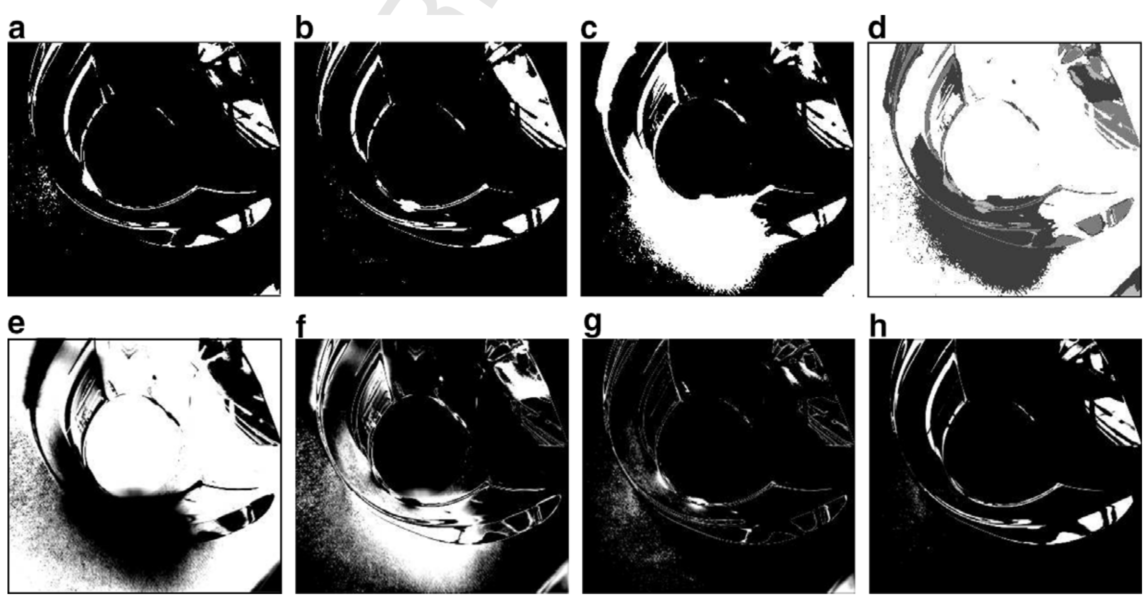

Fig. 9. Results of the binarization, the label image generation, and the fuzzy label image generation after automated determination of thresholds. Results of the binarization, the label image generation, and the fuzzy label image generation after automated determination of thresholds θ_i. (a) Binarization of image in Fig. 7a with $\theta_1 = 243$. (b) Binarization of image in Fig. 7b with $\theta_2 = 225$. (c) Binarization of image in Fig. 7c with $\theta_3 = 227$. (d) Resulting crisp label image. Fuzzy label image with fuzzy membership functions characterizing areas with: (e) no highlight, (f) highlight in one channel, (g) highlight in two channels, and (h) highlight in all three channels.

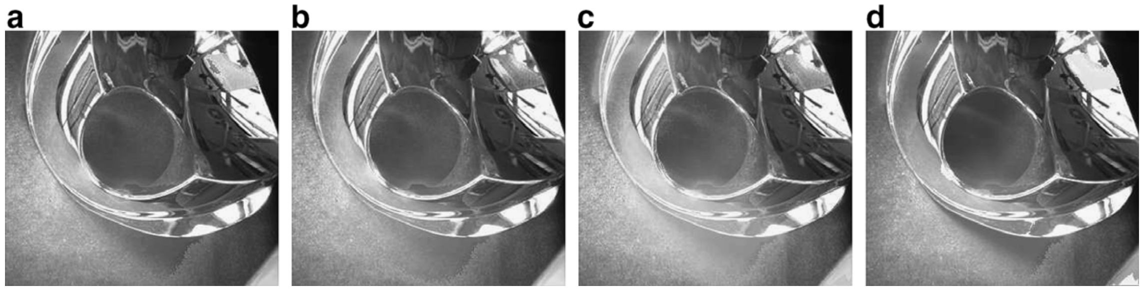

Fig. 10. Results of the utilization of interactive genetic algorithms for the construction of fuzzy measures. Results of the utilization of interactive genetic algorithms for the construction of fuzzy measures. Results obtained on images depicted in Fig. 7 for different types of interactive genetic algorithms and different parametrizations (see Table 1).

Table 1
Type and parametrization of different interactive genetic algorithms used in the computation of the preliminary results depicted in Fig. 10

Fig. 10	GA type	Gen	PCross	PMut	El/PRepl	MType
(a)	Simple	20	0.8	0.1	Elitism	λ
(b)	StSt	8	0.95	0.1	0.9	λ
(c)	StSt	9	0.7	0.048	0.9	λ
(d)	StSt	10	0.81	0.024	0.9	General

Gen: number of generations. PCross: crossover probability. PMut: mutation probability. El: elitism. PRepl: replacement probability. MType: fuzzy measure type. StSt: steady state.

measures (see Table 1). The number of individuals is limited to 10 in order for all of them to fit in the displaying surface of a 17 in. computer monitor. The diversity among the individuals quickly decreases in each generation, i.e. the individuals tend to be equal up to the fifth generation. Although this shortcoming can be controlled (though cannot be avoided) through the crossover and mutation probabilities, this relationship does not seem to be deterministic. The interactive determination becomes tedious for the user up to the seventh generation. The utilization of an estimation of the fitness of each individual, which can then be modified by the user, improves the results (see Fig. 10c–d). The convergence of the genetic search in this case succeeds in a smaller number of generations than in the case where the user "blindly" gives the fitness of each individual (see Fig. 10a–b). The interactive parametrization process described in this section was undertaken by one user.

5.1.3. Construction of the fuzzy measures through GAs

A second simulation pursues the determination of the best GA's parameterization in the construction of the fuzzy measure. Thus a genetic algorithm with different crossover and mutation probabilities are taken into consideration. The genetic algorithm is of type steady state, i.e. a percentage of the population, which is determined by the probability of replacement, is maintained over the different generations. The analysis is conducted for the fitness functions f_1, Eq. (6), f_2, Eq. (7), and f_3, Eq. (8). The evolution of these fitness functions for the best individual of the population in each generation is analyzed for three values of crossover probability and four of mutation probability. The evolution of each fitness function reaching the absolute minimum of all these combinations is depicted in Fig. 11.

Table 2 summarizes the best parameters resulting from the application of each fitness function. The evolution of the fitness function f_1, Eq. (7), does not show any difference among the different values of mutation probability up to a particular number of generations (see Fig. 11b). In this case the fuzzy measures were selected after a subjective evaluation of the resulting images for the last generation.

The fuzzy measure coefficients obtained through the GAs parameterized as stated in Table 2 are selected. Thence the final results are computed (see Fig. 12) based on this parametrization.

5.1.4. Computational cost of the framework's application and the influence of the tolerance factor (ε) on it

The computational cost of the framework presented herein has been analyzed on a computer with a PowerPC G3 processor working at 400 MHz with an implementation developed in Python, an interpreter programming language.[3] The result of this analysis is shown in Fig. 13. The framework operates at approximately 0.1 ms per pixel, if it uses a "crisp" label image. Thus an image of 256×256 pixels is pre-processed in approximately 6.5 s for this configuration.

The execution time of the framework linearly varies with the increment of the tolerance ε (see Fig. 13a). Therefore a trade-off among the value of this parameter and the quality of the system's output have to be undertaken. As it can be observed by comparing Figs. 13b and 12f, a larger tolerance does not necessarily imply a better performance of the system.

5.1.5. Generalization capability of the framework

Fig. 14 shows the input images generated over another object as the one considered so far. An ILFO with the same fuzzy measures found for the object considered up to now is applied on these input images. The results obtained for different fitness functions are depicted in Fig. 15. Taking into consideration that the results are achieved by applying

[3] Interpreter languages are supposed to operate approximately 10 times slower than compiling ones.

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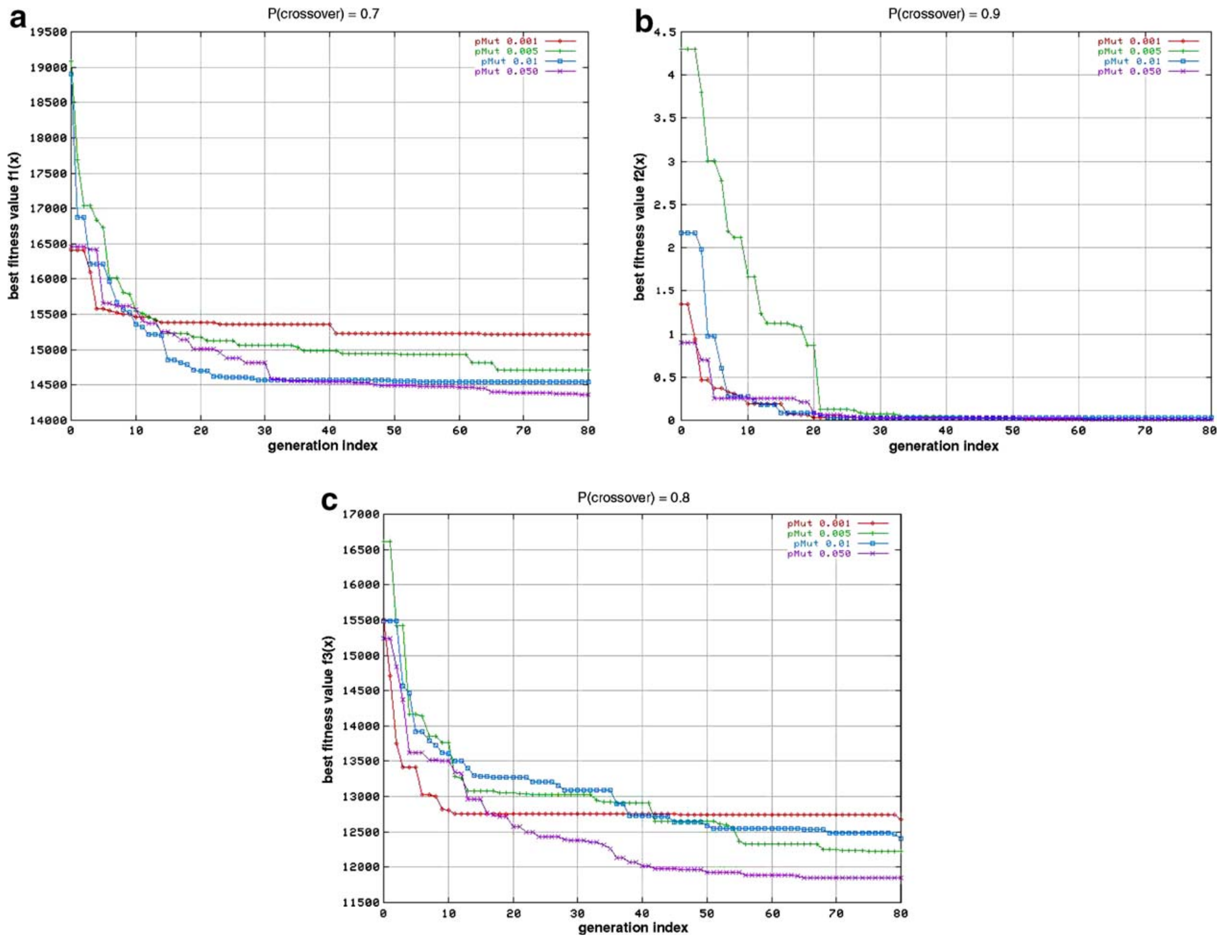

Fig. 11. Convergence of the GA over different generations in the computation of the fuzzy measure coefficients of the ILFO applied for obtaining the images depicted in Fig. 12(a–c). The convergence is shown for the best crossover-mutation combination of each considered fitness function $f_i(x)$ computed for the best individual in each generation. (a) Fitness function f_1 Eq. (6). (b) Fitness function f_2 Eq. (7). (c) Fitness function f_3 Eq. (8).

Table 2
Best parametrization of a steady state genetic algorithm for the construction of a fuzzy measure for different fitness functions f_i.

Parameter	f_1 Eq. (6)	f_2 Eq. (7)	f_3 Eq. (8)
Crossover probability	0.7	0.9	0.8
Mutation probability	0.05	0.005	0.05
Replacement probability	0.9	0.9	0.9
Number of generations	80	63	65
Population size	40	40	40
Result in Fig. 12	(a), (d)	(b), (e)	(c), (f)

the same conditions in the acquisition of the input images, this simulation gives a clear idea of the generalization capability of the here presented framework.

5.1.6. *Objective quality assessment of fusion results*

The quality of the fusion results could be formerly assessed from a subjective point of view (see Figs. 10 and 12). In this section different quality measures would be applied on those results in order to objectively quantize the performance of the framework presented herein. Three different measures have been computed.

First the *weighted fusion quality* and the *edge-dependent fusion quality* indices from [28] are taken into account. These indices are based on the *image quality index* proposed in [29], which reflects the local similarity and the local luminance distortion between two images. This measure is adapted to the problem of image fusion in [28] by applying some features of human perception. Hence the dependence of the quality on the saliency of image elements becomes a weighting factor in the *weighted fusion quality index*. Moreover the importance of edge detection drives the value of the *edge-dependent fusion quality index*.

On the other hand, the *mutual information index* [30] is based on the computation of the mutual entropy among different images. Therefore this index can be understood as a statistical quality measure among image histograms, where the spatial distribution of grayvalues does not play any role. Nevertheless, this measure has been successfully applied in the quality assessment of medical images' fusion. The values of the mentioned quality measures are summarized in Table 3.

The numerical results confirm the subjective inspection. Hence the best results were obtained for the GA parameterization in contrast with the IGA one. Furthermore the

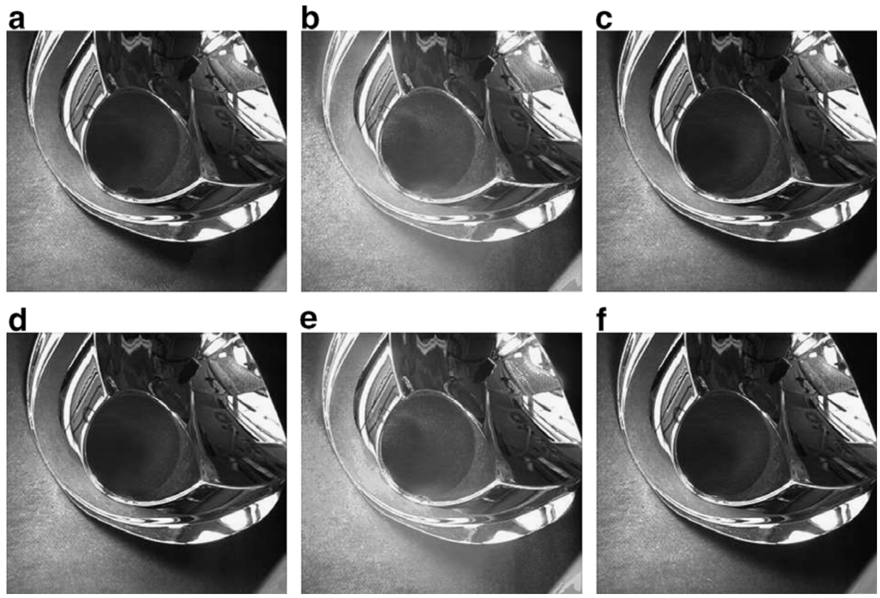

Fig. 12. Final results of an automated system for the visual inspection of headlamp reflectors, where the fuzzy measures are constructed after a GA with different fitness functions and parameterized according to Table 2. The results are obtained for two highlight tolerance (ε) values (see Section 3.2). (a) Fitness function f_1 Eq. (6) and $\varepsilon = 0$. (b) Fitness function f_2 Eq. (7) and $\varepsilon = 0$. (c) Fitness function f_3 Eq. (8) and $\varepsilon = 0$. (d) Fitness function f_1 Eq. (6) and $\varepsilon = 50$. (e) Fitness function f_2 Eq. (7) and $\varepsilon = 50$. (f) Fitness function f_3 Eq. (8) and $\varepsilon = 50$.

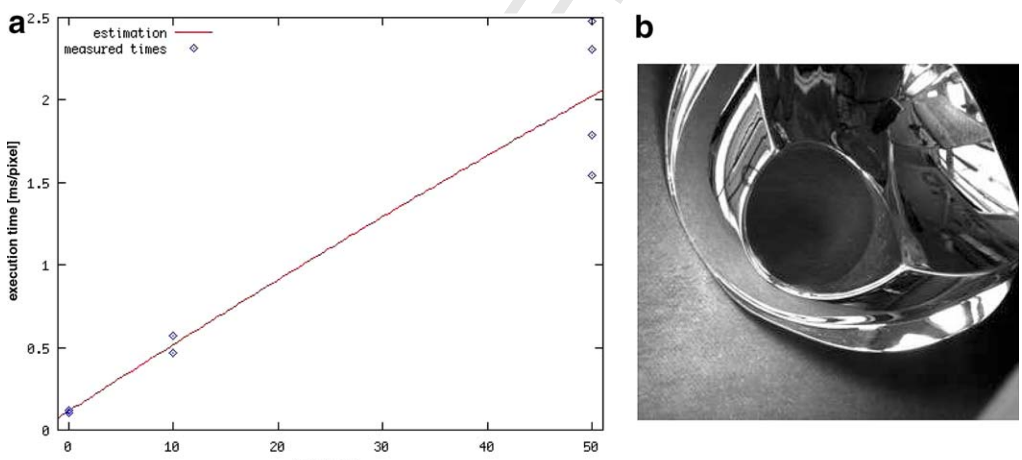

Fig. 13. (a) Estimation of the dependence of the execution time (ms/pixel) of an ILFO based on the CFI with respect to the highlight tolerance (ε) parameter (see Section 3.2). (b) Effect of the tolerance variation (ε) on the final results of the automated pre-processing system. Fuzzy measures are constructed after a GA with the fitness function f_3 (8) and parameterized according to Table 2. Highlight tolerance value $\varepsilon = 10$ (compare with Fig. 12c and f).

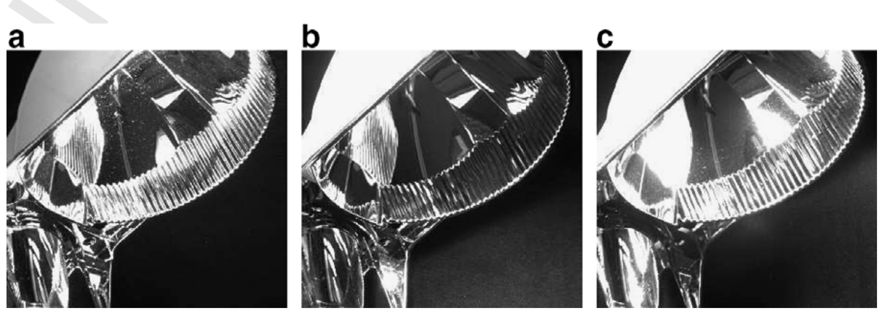

Fig. 14. Input images (of a second object) of the pre-processing stage in a system for the detection of structural faults on automotive headlamp reflectors (item II).

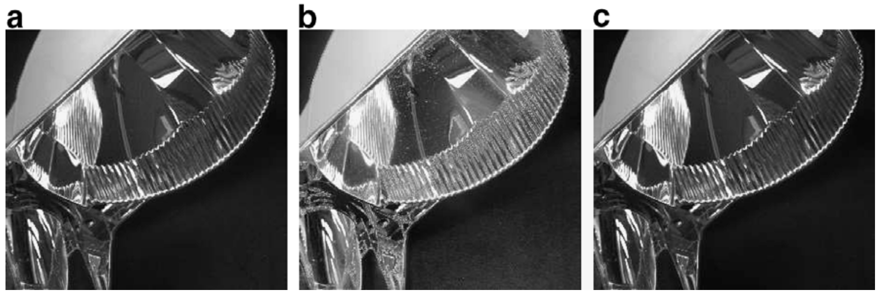

Fig. 15. Final results of the automated pre-processing system, where the fuzzy measures are obtained with a training on the object depicted in Fig. 7. (a) Fitness function f_1 Eq. (6). (b) Fitness function f_2 Eq. (7). (c) Fitness function f_3 Eq. (8).

Table 3
Objective comparison of fusion results through the application of three different quality measures, namely the *weighted fusion quality index* (Q_W) [28], *edge-dependent fusion quality index* (Q_E) [28], and the *mutual information index* (MI) [30], to some of the fusion results depicted in Figs. 10 and 12

	GA Fig. 12						IGA Fig. 10	
	f_1 Eq. (6)		f_2 Eq. (7)		f_3 Eq. (8)			
	$\varepsilon = 0$	$\varepsilon = 50$	$\varepsilon = 0$	$\varepsilon = 50$	$\varepsilon = 0$	$\varepsilon = 50$	Sim	StSt
Q_W	0.8446	**0.8456**	0.7971	0.8101	0.8198	0.8368	0.8166	0.7742
Q_E	0.6838	**0.6857**	0.5803	0.6015	0.6529	0.6758	0.6270	0.5493
MI	0.2653	0.2643	0.2313	0.2323	**0.4096**	0.2580	0.2335	0.2617
Fig.	12a	12d	12b	12e	12c	12f	10a	10d

The corresponding ILFOs were parameterized by applying: first genetic algorithms (GA) w.r.t. the three fitness functions f_i and two tolerance (ε) values; second two types of interactive genetic algorithms (IGA), namely based on a simple (Sim) and a steady state (StSt) GAs. Maximal values for each index are shown in bold typing.

fitness functions f_1 and f_3 perform better than f_2. The results of these two fitness functions are similar. It is worth mentioning that following the numerical results the tolerance factor is more important, when using f_1. In this context the reader should take into account the increment in the computational cost that is associated with an increment of the tolerance value ε (see Section 5.1.4).

5.2. Inspection of plastic bundled packages

The automated inspection of a consumer good is presented in this section (see Fig. 16). It shows the possible extension of the framework presented herein for the pre-processing of color images. The highlights are produced by the plastic bundle of the object. Three different

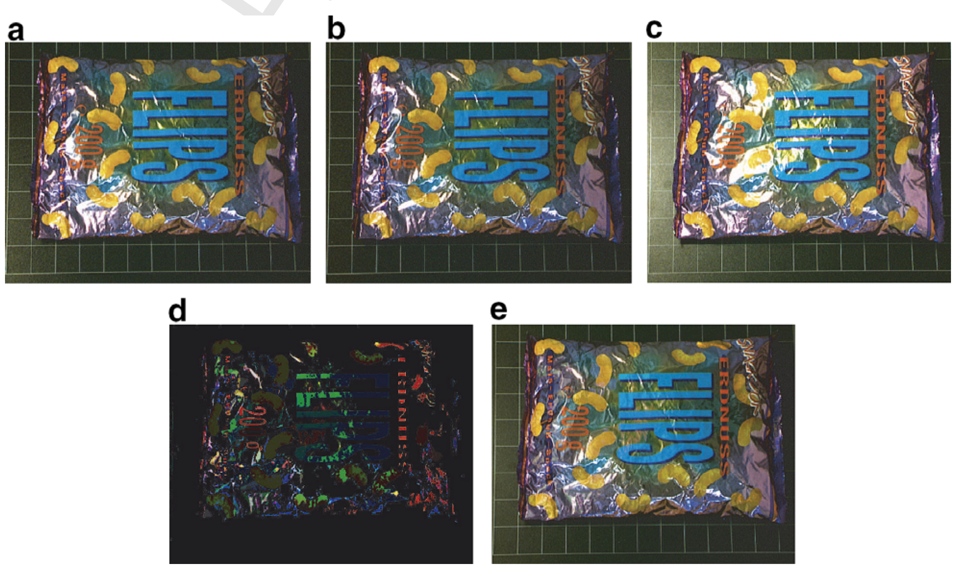

Fig. 16. Results of the extension of the framework presented herein for the pre-processing of color images in a market basket recognition prototype. (a–c) Input image set. (b) Label image. (c) Result of the application of an ILFO extended to color images.

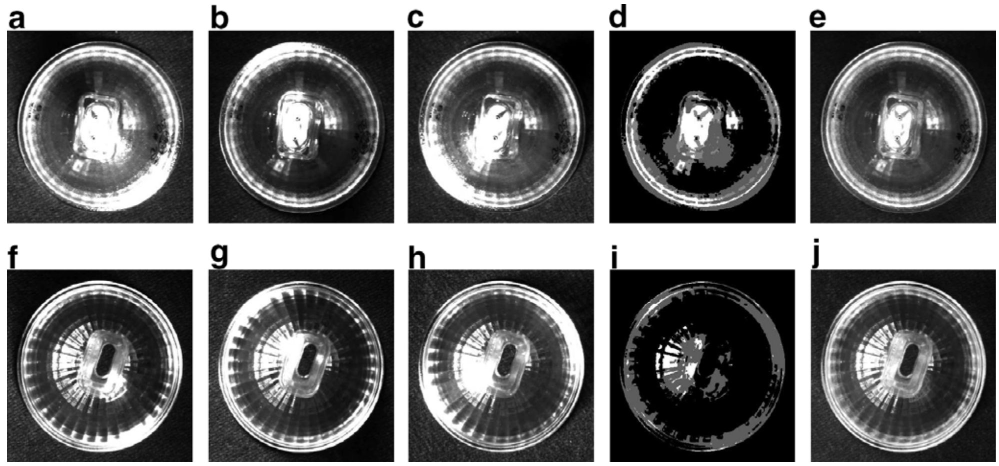

Fig. 17. Input images of the pre-processing stage in a system for the detection of structural faults on halogen bulbs.

images of the package are generated and depicted in Fig. 16a–c.

The mentioned extension is achieved by applying an ILFO to each of the color channels of the input image set. First a mask is generated. The mask image, where the fuzzy measures are localized, is depicted in Fig. 16d. It is worth pointing out the limitation of the framework w.r.t. to the inspection of free deformable objects (see Fig. 16e). The pre-processing of such objects demands a set of input images with larger cardinality. This increment can reduce the number of redundant highlight areas among the input images.

5.3. Inspection of halogen bulbs

The results obtained in the pre-processing of a structural fault detection system, which was applied on halogen bulbs, are described in the following. The input images of the system are shown in Fig. 17a–c and f–h.

The generated mask images can be observed in Fig. 17d and i. The obtained results are depicted in Fig. 17e and j. The consequence of having redundant reflections on all images of the input image set can be observed on the depicted results. The reflection cannot be suppressed in those areas where all images present one, since there is no image information about the underlying structure. In this case the redundant reflection, was caused by an external light. The employed image acquisition module do not use any protection against such influences. This one of the shortcomings of the framework presented herein.

6. Conclusions

The framework for highlights filtering presented in [5] has been systematically analyzed herein. Intelligent Localized Fusion Operators, which generalize the employment of the fuzzy integral for image fusion, are based on the local definition of the fuzzy measures. Thus the formalization of this operator, which is undertaken in this paper, allows employing the operator as a pre-processing stage in different automated visual inspection systems. Furthermore, the results attained by such a pre-processing stage are described. Particularly the utilization of peak dynamic analysis as binarization procedure, the employment of Interactive genetic algorithms and of genetic algorithms for the parametrization of the fuzzy integral, and the generalization capability of the framework, have been analyzed.

The application of an histogram analysis based on the concept of peak dynamics demonstrates to be a very helpful tool in the binarization of images corrupted by highlights and therefore in the automation of the procedure. It is worth mentioning that the values of the threshold θ automatically obtained through the computation of the peak dynamics are nearly the same as those heuristically set in [5] through the visual analysis of the histograms.

The application of interactive genetic algorithms demonstrated to be an interesting alternative to the application of genetic algorithms. Nevertheless its usage should be improved for obtaining satisfactory results. This fact was numerically proven through the application on the resulting images of different quality measures employed in image fusion. Since the best parameterization of the genetic algorithms has been proposed herein, this methodology remains hitherto the best option for automatically defining the weighting parameters of the system. The application of a fitness function minimizing the variance of the grayvalue histogram outperforms other alternatives as demonstrated both by the numerical analysis and the subjective evaluation of the results obtained with this fitness function. Therefore, its application allows the system to operate full automated with a very good performance in the filtering of highlights. The tolerance value ε constitutes the only free parameter in the system. Taking the tolerance ε can become helpful in the improvement of the results. Nevertheless a performance trade-off between its computational cost and the real improvement have to be undertaken in real appli-

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cations. It is lastly worth pointing out that the results are exclusively dependent on the acquisition adjustments, what proves the generalization capability of the framework.

As it has been shown the performance of the pre-processing system improves with the increment of the flexibility of the fusion operator. In this context Intelligent Localized Fusion Operators offer novel possibilities for solving challenging applications. The performance of the pre-processing system can be improved by taking a more systematic and controlled acquisition of images into consideration. The utilization of a special illumination station can allow the generation of a larger multi-dimensional image set with less redundancy among the images of the input image set. Furthermore the reflections of the environment on the object surfaces can be avoided in this fashion as well. This is the most immediate goal to be attained in the future in order to improve the pre-processing capability of the system.

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