New fuzzy local contrast measures: definitions, evaluation and comparison

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***Abstract*—In this contribution the concept of a local contrast of a fuzzy relation with the use of a consensus measure is introduced. A construction method of such local contrast using aggregation functions and fuzzy implications is considered. Other construction methods using similarity measure are also pointed out. Several examples of local contrasts are provided. The usability of introduced local contrast measures is evaluated by applying them in image processing for salient region detection.**

***Index Terms*—contrast measures, aggregation functions, saliency detection, similarity measures**

I. Introduction

The concept of a local contrast of a fuzzy relation makes sense in any field where it is necessary to take into account the influence of neighboring elements on the element itself, e.g.: decision making, approximate reasoning, pattern recognition, image processing. In these application areas the characteristics of neighboring data points are as important as the data itself.

A local contrast is a measure of the variation among the membership degrees of elements in a specific region of a fuzzy relation. In this contribution we follow the notion of a contrast given axiomatically in [1]. We provide a new construction method with the use of a consensus concept (cf. [2]) which may be treated as a measure of agreement among the inputs. Moreover, we give several examples of local contrast based on the construction method involving aggregation functions and fuzzy implications. We also give examples of local contrast with the similarity measure involved. Furthermore, we mention the concept of a total contrast of a fuzzy relation where examples of total contrast may be obtained by aggregating the local contrasts. To evaluate introduced fuzzy contrasts on real-world data we propose applying them in salient region detection problem, which relies greatly on detecting regions with high contrast [3]. Obtained saliency maps are binarized with diverse thresholding strategies involved (cf. [4], [5]) and compared to the human-annotated ground truth. The obtained results prove effectiveness of the new examples.

The paper is organized as follows. In Section 2, basic notions related to fuzzy connectives such as negations and implications are recalled. Next, in Section 3, local contrast is studied providing the construction methods and several examples. Finally, in Section 4 results of applying proposed definitions on images from MSRA10K dataset [5] are presented. The proposed definitions are evaluated using accuracy, precision and recall.

II. Preliminaries

We recall the notion of a fuzzy negation and an aggregation function on the unit interval $[0,1]$.

Definition 1 (cf. [6])**.** A fuzzy negation N is a decreasing function $N:[0,1]\to[0,1]$ such that $N(0)=1$ and $N(1)=0$. A fuzzy negation is strong if $N(N(a))=a$ for all $a\in[0,1]$.

Definition 2 ([7], pp. 2, 9)**.** A fuzzy implication $I:[0,1]^2\to[0,1]$ is a decreasing function in the first component and increasing function in the second component and $I(1,0)=0$, $I(0,1)=I(0,0)=I(1,1)=1$. A fuzzy implication fulfils:

- identity principle, if $I(a,a)=1$ for $a\in[0,1]$.
- contraposition with respect to a fuzzy negation N, if

$$I(a,b)=I(N(b),N(a)),\quad a,b\in[0,1].$$

Examples of fuzzy implications I satisfying the identity principle and contraposition with respect to the classical fuzzy negation $N(a)=1-a$ are:

- Łukasiewicz implication -

$$I_{LK}(a,b)=\begin{cases}1, & \text{if } a\le b\\ 1-a+b, & \text{otherwise;}\end{cases}$$

- Fodor implication -

$$I_{FD}(a,b)=\begin{cases}1, & \text{if } a\le b\\ \max(1-a,b), & \text{otherwise;}\end{cases}$$

- Rescher implication -

$$I_{RS}(a,b)=\begin{cases}1, & \text{if } a\le b\\ 0, & \text{otherwise;}\end{cases}$$

- Reichenbach implication -

$$I_{RC}(a,b)=1-a+ab;$$

- Kleene-Dienes implication -

$$I_{KD}(a,b)=\max(1-a,b).$$

Definition 3 (cf. [8], Definition 1)**.** Let $n\ge 2$. $A:[0,1]^n\to[0,1]$ is said to be an aggregation function if it is increasing and fulfils boundary conditions $A(0,...,0)=0$, $A(1,...,1)=1$.

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There are several subfamilies of aggregation functions. One of them are n-dimensional overlap functions or recently introduced general overlap functions.

Definition 4 ([9]). $A : [0,1]^n \to [0,1]$ is said to be an n-dimensional overlap function if the following properties hold:

(O1) A is commutative;
(O2) $A(\overrightarrow{a}) = 0$ if and only if $\prod_{i=1}^n a_i = 0$;
(O3) $A(\overrightarrow{a}) = 1$ if and only if $\prod_{i=1}^n a_i = 1$;
(O4) A is increasing;
(O5) A is continuous,

where $\overrightarrow{a} = (a_1, ..., a_n)$.

Examples of n-dimensional overlap functions (cf. [9]) are the product (3) and the minimum powered by p element-wise (1) which will be applied in our considerations. Recently, a more general version of the notion of an overlap function was introduced.

Definition 5 ([10]). $A : [0,1]^n \to [0,1]$ is said to be a general overlap function if the following properties hold:

(GO1) A is commutative;
(GO2) if $\prod_{i=1}^n a_i = 0$, then $A(\overrightarrow{a}) = 0$;
(GO3) if $\prod_{i=1}^n a_i = 1$, then $A(\overrightarrow{a}) = 1$;
(GO4) A is increasing;
(GO5) A is continuous.

The difference between the class of n-dimensional overlap functions and the class of general overlap functions is that the former has sufficient and necessary boundary conditions (GO2) and (GO3) while the latter has sufficient conditions. Mathematically, this means that the class of general overlap function may have zero-divisors and one-divisors while n-dimensional overlap functions are without zero-divisors and one-divisors.

An example of a general overlap function ([10]) is given by (2) which is not an n-dimensional overlap function.

Since the presented concepts for fuzzy relations are related to possible applications in image processing we present them on a finite domain.

Definition 6 ([11]). Let $X = \{0, 1, ..., N-1\}$ and $Y = \{0, 1, ..., M-1\}$ be two finite sets. A fuzzy relation on $X \times Y$ is a fuzzy set of the type

$$R = \{((x,y), R(x,y)) | (x,y) \in X \times Y\},$$

with $R : X \times Y \to [0,1]$.
Given a fuzzy relation R, its complement is given by

$$NR = \{((x,y), NR(x,y)) | (x,y) \in X \times Y\},$$

where N is a strong fuzzy negation.

In image processing, a grayscale image of $N \times M$ pixels may be interpreted as a collection of $N \times M$ elements arranged in rows and columns. A numerical value representing intensity, chosen from the set $\{0, 1, 2, ..., L-1\}$, is assigned to each element. An image Q is just a matrix so it may be represented as a fuzzy relation R on a finite set such that the membership degree of each element (pixel) is its intensity divided by $L-1$. For a color image, its channels can be independently represented in the same way.

III. Local contrast

In the paper [1] several examples of local contrast were examined and properties required for this notion in literature were studied. This led the authors in [1] to introduce the axiomatical description of a local contrast which should fulfill the following axioms.

Definition 7 ([1]). A local contrast LC associated with a strong negation N is a real function on $X \times Y$ such that:
(LC1) $0 \leq LC(x,y) \leq 1$ for all $(x,y) \in X \times Y$;
(LC2) If the membership degrees of all the elements of the submatrix centered on (x,y) are identical, then $LC(x,y) = 0$. That is, if $R(x-i, y-j) = q$ with $q \in [0,1]$ constant for all $i,j = -n; ...; 0; ...; n$, then $LC(x,y) = 0$.
(LC3) If in the submatrix centered on (x,y) there is at least one element with null membership and at least one element with a membership degree of one, then $LC(x,y) = 1$.
(LC4) The local contrast of (x,y) does not change if for all $i,j = -n; ...; 0; ...; n$ we take $N(R(x-i, y-j))$ instead of $R(x-i, y-j)$.

We present some examples of a local contrast.

Example 1 ([1]). Let N be a strong negation. Thus LC for $(x,y) \in X \times Y$ may be defined in the following way:

$$LC_{inf}(x,y) = \begin{cases} 1 & \text{if in the submatrix there exist} \\ & \text{at least one element with} \\ & \text{the membership equal to 1} \\ & \text{and another equal to 0;} \\ 0 & \text{otherwise.} \end{cases}$$

$$LC_{sup}(x,y) = \begin{cases} 0 & \text{if the memberships of all} \\ & \text{elements in the submatrix} \\ & \text{are the same;} \\ 1 & \text{otherwise.} \end{cases}$$

$$LC_{HB1}(x,y) =$$

$$\begin{cases} 0 & \text{if the memberships of} \\ & \text{all elements in the} \\ & \text{submatrix are the same;} \\ 1 & \text{if in the submatrix there} \\ & \text{exist at least one} \\ & \text{element with the} \\ & \text{membership equal to 1} \\ & \text{and another equal to 0;} \\ \frac{\sum\limits_{i,j=-n}^{n} R(x-i,y-j) N(R(x-i,y-j))}{\text{size of the submatrix}} & \text{otherwise.} \end{cases}$$

$$LC_{HB2}(x,y) = \max_{i,j=-n}^{n} R(x-i, y-j) - \min_{i,j=-n}^{n} R(x-i, y-j).$$

Let us note that LC_{inf} and LC_{sup} provide bounds for any local contrast, i.e.

$$LC_{inf} \leq LC \leq LC_{sup}.$$

Total contrast of a fuzzy relation may be defined in the following manner.

Definition 8 ([1]). Let N be a strong negation. A total contrast TC associated with N is a real function on $FR(X \times Y)$ such that:
(TC1) $0 \leq TC(R) \leq 1$;
(TC2) If all elements of the fuzzy relation R have the same membership degree, then $TC(R) = 0$;
(TC3) If R is a crisp relation such that there exists at least one element with membership equal to one and another with membership equal to zero, then $TC(R) = 1$;
(TC4) The total contrast of a fuzzy relation and that of its negation (by N) are the same; that is, $TC(R) = TC(N(R))$.

In the following proposition we show that aggregating local contrasts will produce a total contrast as long as we choose the aggregating function properly. Usually aggregation functions are required to be increasing (cf. Definition 3). However, we may also drop this requirement to consider aggregation function as the one which combines the single values into one value.

Proposition 1 ([1]). *Consider $R \in FR(X \times Y)$, and let LC be a local contrast associated with a strong negation N (in the sense of definition of total contrast TC). Then let $F : \bigcup_{m \in N} [0,1]^m \to [0,1]$ be a function such that:*
(1) $F(0,...,0) = 0$ and $F(1,...,1) = 1$.
(2) If $a_i \in \{0,1\}$ for all $i \in \{1,...,m\}$, and there exist at least one component $a_p = 1$ and another component $a_q = 0$ with $p, q \in \{1,...,m\}$, then $F(a_1,...,a_m) = 1$. Under these conditions,

$$TC(R) = F_{x=0,...,N-1,y=0,...,M-1} LC(x,y)$$

is a total contrast associated with the strong negation N.

Example 2 ([1]). The following are examples of functions fulfilling assumptions of Proposition 1:
$F(a_1,...,a_m) = \max(a_1,...,a_m)$.

$$F(a_1,...,a_m) = \begin{cases} 1, & \text{if } a_i \in \{0,1\} \text{ for all} \\ & i \in \{1,...,m\} \\ & \text{and there are at least one} \\ & a_p = 1 \text{ and one } a_q = 0 \\ & \text{such that } p,q \in \{1,...,m\} \\ \frac{1}{m}\sum\limits_{i=1}^{m} a_i, & \text{otherwise.} \end{cases}$$

Example 3. Examples of total contrast are the following.

Maximum of local contrast of all elements of the matrix

$$TC_1(R) = \max_{x=0,...,N-1; y=0,...,M-1} LC(x,y).$$

$TC_2(R)$=

$$\begin{cases} 1, & \text{if } LC(x,y) \in \{0,1\} \text{ for} \\ & \text{all } (x,y) \in X \times Y \text{ and} \\ & \text{there are at least one} \\ & (x,y) \text{ that } LC(x,y) = 1 \\ & \text{and another } (x,y) \\ & \text{that } LC(x,y) = 0 \\ \frac{1}{N \cdot M}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} LC(x,y), & \text{else .} \end{cases}$$

In the next part of the paper we will concentrate on the notion of a local contrast.

In the paper [2] the concept of a consensus measure was analyzed in the context of decision making. Consensus may be treated as a measure of agreement among inputs. As a result there were proposed two minimal axioms that a consensus measure should fulfill.

Definition 9 ([2]). A function $C : [0,1]^n \to [0,1]$ is said to be a consensus measure if it satisfies the following properties:
(C1) (Unanimity) For all $a \in [0,1]$ it holds that $C(a,a,...,a) = 1$,
(C2) (Minimum consensus for n = 2) For the special case of two inputs it holds that $C(0,1) = C(1,0) = 0$.

Unanimity (C1) is a natural requirement for consensus which says that the agreement is total in the case of the same inputs. Minimum consensus (C2) means that for the two totally different inputs we obtain total disagreement, i.e. consensus equals zero. Since we would like to apply the consensus measure in image processing issues, in the context of describing the local contrast, we propose a modified version of the consensus where the axiom (C2) is replaced with its adequate version for the case of n-argument inputs. We will call this version by a strict consensus measure.

Definition 10. A function $C : [0,1]^n \to [0,1]$ is a strict consensus measure if it satisfies the following properties:
(C1) For all $a \in [0,1]$ it holds that $C(a,a,...,a) = 1$,
(C2') If $a_k = 0$ and $a_l = 1$ for some $k, l \in \{1,...,n\}$, then $C(a_1,...,a_n) = 0$.

The following example justifies the adjective 'strict' in the new version of the consensus.

Example 4 ([12]). The following is a consensus measure but it is not a strict consensus measure

$$C(a_1,...,a_n) = 1 + \frac{1}{n}\sum_{i=1}^{n} log_2(1 - |a_i - \overline{a}|),$$

where $\overline{a} = \frac{1}{n}\sum_{i=1}^{n} a_i$.

Consensus measure may have some additional properties (cf. [2]). We recall only one of them.

Definition 11 (cf. [2]). A consensus measure (a strict consensus measure) C is said to be reciprocal if for a strong negation N, it holds

$$C(a_1,...,a_n) = C(N(a_1),...,N(a_n))$$

for all $a_1, ..., a_n \in [0,1]$.

Below we remind a construction of the consensus measure with the use of an aggregation function and a fuzzy implication.

Proposition 2 ([2]). *Let M denote an averaging aggregation function and I denote a fuzzy implication satisfying the identity principle. The following is a consensus measure*

$$C(a_1, ..., a_n) = \frac{1}{1-K}\left(M^n_{i,j=1,i\neq j} I(a_i, a_j) - K\right),$$

where

$$K = \min_{b\in[0,1]^n} M^n_{i,j=1,i\neq j} I(b_i, b_j).$$

It is easy to see the following simplified dependence.

Proposition 3. *If an aggregation function M has a zero element zero, I denotes a fuzzy implication satisfying the identity principle, then C defined in the following way*

$$C(a_1, ..., a_n) = M^n_{i,j=1,i\neq j} I(a_i, a_j)$$

is a strict consensus measure.

If for example $M = \min$ or M is a weighted geometric mean, then C is a strict consensus measure for adequate fuzzy implications I.

Proposition 4 ([2]). *Let M denote a symmetric averaging aggregation function and I denote a fuzzy implication satisfying the identity principle and contraposition with respect to a strong negation N. Then*

$$C(a_1, ..., a_n) = \frac{1}{1-K}\left(M^n_{i,j=1,i\neq j} I(a_i, a_j) - K\right),$$

where

$$K = \min_{b\in[0,1]^n} M^n_{i,j=1,i\neq j} I(b_i, b_j)$$

is a reciprocal consensus measure.

We will use the following modification of the above proposition.

Proposition 5. *Let $M : [0,1]^n \to [0,1]$ denote a symmetric aggregation function with a zero element zero and I denote a fuzzy implication satisfying the identity principle and contraposition with respect to a strong negation N. Then*

$$C(a_1, ..., a_n) = M^n_{i,j=1,i\neq j} I(a_i, a_j)$$

is a reciprocal strict consensus measure.

Since consensus is a measure of agreement among the given values and a local contrast, on the contrary means a disagreement among inputs, we propose to construct a local contrast as a negation of the consensus measure over the given set of values. It is easy to verify that the following dependence holds.

Proposition 6. *Let $R \in FR(X\times Y)$, C be a reciprocal strict consensus measure with respect to a strong fuzzy negation N. Then $LC : X \times Y \to [0,1]$ is a local contrast, where for all $(x,y) \in X \times Y$*

$$LC(x,y) = N(C^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(R(x-i, y-j))).$$

From Propositions 5 and 6, for the classical fuzzy negation $N(a) = 1-a$, we directly obtain

Corollary 1. *Let $R \in FR(X\times Y)$, M be an aggregation function and I be a fuzzy implication that both satisfy assumptions of Proposition 5. Then the operation*

$$LC(x,y) =$$

$$1-(M^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j), R(x-k,y-l)))$$

is a local contrast.

Based on Corollary 1 we may obtain the following examples of local contrasts.

Example 5. Let $(x,y) \in X \times Y$.
For $M = \min$ and $I = I_{LK}$ we have

$$LC_1(x,y) = 1-$$

$$(\min^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(\min(1, 1-R(x-i,y-j)+R(x-k,y-l)))$$

$$= \max^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(\max(0, R(x-i,y-j)-R(x-k,y-l))).$$

If M is the geometric mean and $I = I_{LK}$ we have

$$LC_2(x,y) = 1-$$

$$(G^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(\min(1, 1-R(x-i,y-j)+R(x-k,y-l))),$$

where

$$G(a_1, ...a_m) = \sqrt[m]{a_1 \cdot ... \cdot a_m},$$

is the geometric mean.

For $M = \min$ and $I = I_{FD}$ we have

$$LC_3(x,y) =$$

$$1-(\min^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j), R(x-k,y-l))).$$

If M is the geometric mean and $I = I_{FD}$ we have

$$LC_4(x,y) =$$

$$1-(G^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j), R(x-k,y-l))).$$

If Mp is the minimum powered by p element-wise and $I = I_{FD}$ we have

$$LC_5(x,y) =$$

$$1-(Mp^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j), R(x-k,y-l))),$$

where

$$Mp(a_1, ..., a_n) = \min^n_{i=1}\{a_i^p\}, \quad p > 0. \tag{1}$$

For Mp and $I = I_{LK}$ we have

$$LC_6(x,y) =$$

$1-(Mp^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j),R(x-k,y-l)))$.

For Mp and $I = I_{RC}$ we have

$$LC_7(x,y) =$$

$1-(Mp^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j),R(x-k,y-l)))$.

For Mp and $I = I_{KD}$ we have

$$LC_8(x,y) =$$

$1-(Mp^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j),R(x-k,y-l)))$.

If M is a GM_{Luk} general overlap function where

$$GM_{Luk}(a_1,...,a_n) = \sqrt[n]{\prod_{i=1}^{n} a_i} \cdot (\max\{\sum_{i=1}^{n} a_i - (n-1), 0\}) \tag{2}$$

and $I = I_{LK}$ we have

$$LC_9(x,y) = 1-$$

$(GM_{Luk}{}^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j),R(x-k,y-l)))$.

If M is the product

$$P(a_1,...,a_n) = \prod_{i=1}^{n} a_i \tag{3}$$

and $I = I_{LK}$ we have

$$LC_{10}(x,y) =$$

$1-(P^n_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}(I(R(x-i,y-j),R(x-k,y-l)))$.

In another method of construction of the local contrast we use the concept of a similarity S which may be treated as one of the ways of measuring agreement between the input elements.

Definition 12 ([13])**.** A function $S : (FR(X))^2 \to [0,1]$ is called a similarity measure, if S has the following properties:
(SP1) $S(A,B) = S(B,A)$;
(SP2) $D(D,D^c) = 0$, for $D \in P(X)$;
(SP3) $S(A,A) = 1$;
(SP4) if $A \leq B \leq C$, then
$S(A,B) \geq S(A,C)$ and $S(B,C) \geq S(A,C)$
for $A,B,C \in FR(X)$.

Example 6. Let $(x,y) \in X \times Y$, $I = I_{FD}$ and S be a similarity measure $S(a,b) = \min(I(a,b), I(b,a))$. Then

$$LC_{11}(x,y) =$$

$$\max_{i,j=-n}^{n} S(1, R(x-i,y-j)) - \min_{i,j=-n}^{n} S(0, 1-R(x-i,y-j)) =$$

$$\max_{i,j=-n}^{n} I(1, R(x-i,y-j)) - \min_{i,j=-n}^{n} I(1-R(x-i,y-j), 0)$$

is the local contrast.

If in LC_{11} we use implication $I = I_{LK}$ then we call the obtained local contrast by LC_{12}.

We propose also another construction method with the notion of a similarity measure involved. For $S(a,b) = \min(I(a,b), I(b,a))$ and $I = I_{LK}$ we build the following local contrast

$$LC_{13}(x,y) = 1-$$

$$(\min_{i,j,k,l=-n,(i\neq k \text{ or } j\neq l)}^{n} S(R(x-i,y-j), R(x-k,y-l)).$$

If in LC_{13} we use implication $I = I_{FD}$ then we call the obtained local contrast by LC_{14}.

IV. Contrast evaluation

Some of the most common pixel-wise operators in digital photography are the ones performing manipulation of contrast or tone [14]. It is common to use these techniques for contrast enhancement to make photographs look either more attractive or more interpretable. A substantial change of contrast in the image, regardless of the existence of chromaticity (in color images) or absence of one (in grayscale images), can be easily observed by a human (Figure 1).

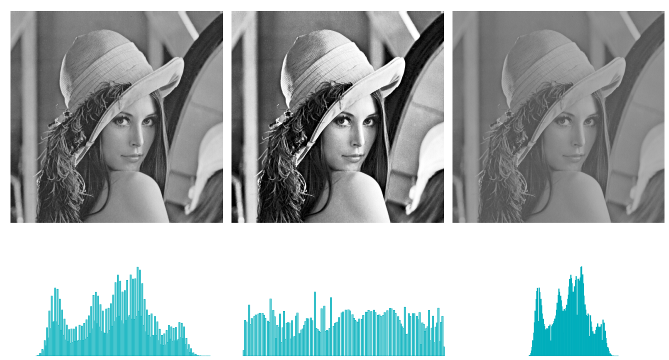

Fig. 1. The Lena images and computed histograms: original contrast (left), image with increased contrast (center) and decreased contrast (right). Contrast adjustments was performed by manipulation of image histogram.

However, local contrast measure is not a strictly defined concept and many different contrasts were proposed [15]. As a consequence, it is difficult to state that a particular contrast definition is correct and to provide a direct comparison between them. It is worthwhile to mention that the majority of contrast enhancement does not define a specific contrast term, but rather exploit the under-utilized regions of the dynamic range [16], for instance, using histogram modification or transform-based techniques.

The salient region detection problem relies heavily on the concept of image contrast [3] and has commonly accepted measures of solution quality. Therefore we propose to evaluate introduced fuzzy contrasts on real-world data by applying them in a salient region detection problem. We believe that evaluating the quality of obtained saliency maps will give us a clue about the usefulness of local contrast definitions and also possibility to compare multiple ones.

A. Saliency detection

Salient region detection, simply called saliency detection is a technique used as the first step in many applications: object-based image retrieval, adaptive content delivery, adaptive region-of-interest based image compression, and smart image resizing [4]. The salient regions are described as more conspicuous in a sense of their contrasts than their surroundings. The salient region could be also intuitively understood as a region that is more visually distinctive to the observer than others [17]. Visual saliency is related closely to human perception and processing of visual stimuli. Many disciplines including cognitive psychology, neurobiology and computer vision study this phenomenon [5]. A number of studies have shown that human cortical cells are highly responsive to high contrast stimuli in their receptive fields [18].

There are a few research topics closely related to saliency detection. Fixation prediction studies try to predict where humans look - the output of these models are usually sets of fixation points. On the other hand, object proposal methods try to generate a set of (typically overlapping) rectangles, often called bounding boxes, describing regions that may represent certain objects. These methods are often used as a preprocessing technique to avoid exhaustive sliding window detection on entire images. All of the methods require some consistent data to evaluate the performance metrics, thus many public datasets were proposed to challenge saliency detection models. The datasets contain manually or automatically obtained labels (in the case of fixation prediction problem ground-truth is usually obtained by eye-tracking device). Sample images and different types of ground truth data are presented in Figure 2.

Fig. 2. Sample images from saliency detection and fixation prediction datasets [5][19]. Top row - input images, bottom row - different types of ground truth data, from left to right: human-annotated bounding box, human annotated pixelwise, eye-tracking results.

There are many approaches for saliency detection, a comprehensive survey of the methods and datasets is provided by [17]. The main two groups are: biologically inspired and purely computational. All methods, however, are "determining local contrasts of image regions with their surroundings". The differences are in the techniques and selecting image information (color, intensity, orientation) [4]. Recently, with the growing popularity of convolutional neural networks, machine learning-based methods were proposed [20].

In our experimental approach we use new fuzzy local contrast definitions to obtain saliency maps for images from the MSRA10K dataset [5]. The dataset is widely used among researchers and provides accurate pixel-wise manually obtained ground truth labeling. Since high variability in color or luminance of neighbouring pixels often contributes to significant visual distinctiveness of a region we attempt to utilize that property for testing these new fuzzy contrasts defined with different aggregation functions.

B. Image preprocessing and saliency map computation

The images were first converted from RGB to CIELAB color space given its perceptual accuracy. After that the color space was fuzzified, according to the formula:

$$\begin{cases} l = \frac{l}{\max l} \\ a = \frac{a+127}{\max a} \\ b = \frac{b+127}{\max b} \end{cases}$$

where fuzzified color is expressed as three values: l for the luminance (from black to white), a from green to red, and b from blue to yellow. In the fuzzification process $\max$ should be understood as maximum value in the image.

To compute saliency map each image was divided into windows, similar to [21] and [3]. For each $m \times n$ window local contrast of each channel (l, a, and b respective) was computed according to our formulas. The size of the window controls it's sensitivity - decrease in m or n makes the window more sensitive to color change. Next, the channels were combined together to form final saliency maps. At the end the image was thresholded using several algorithms - Otsu method was chosen as the best performing one. The result is a binary mask M (Figure 3.), where white regions are considered to be the regions of interest (saliency regions).

C. Local contrast evaluation metrics

We use precision, recall and accuracy, which are universally-agreed measures for evaluating salient object detection algorithms [17]. The provided dataset contains provided by manual annotation, accurate salient object ground-truth labeling for the images. It is worth mentioning that ground-truth data needs to be in this case down-sampled to match the resolution of computed saliency maps. Having computed binary mask M and ground-truth G, the measures are defined as follows:

$$Precision = \frac{|M \cap G|}{|M|}$$

$$Recall = \frac{|M \cap G|}{|G|}$$

$$Accuracy = \frac{|M \cap G|}{|M|}$$

Evaluation of the proposed contrasts on the selected images from MSRA10K dataset averaged among different window sizes ($5 \times 5, 10 \times 10$) is presented in Table 1.

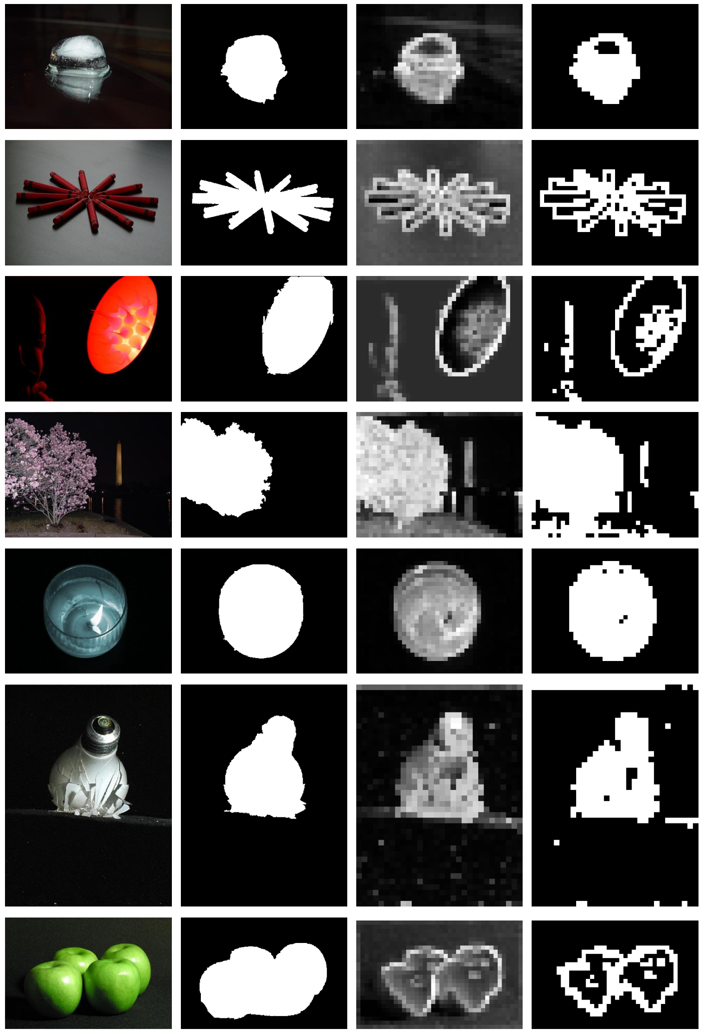

Fig. 3. From left to right: Original image, ground truth, computed saliency image using best performing local contrast, binarized saliency map.

TABLE I. Averaged results

Contrast	p	Precision	Recall	Accuracy
LC_7	2.0	0.795260	0.708756	**0.874853**
LC_7	0.5	0.837872	0.594712	0.871262
LC_7	3.0	0.775138	0.736035	0.870351
LC_8	0.5	0.815778	0.604762	0.861231
LC_5	0.5	0.815778	0.604762	0.861231
LC_6	3.0	0.801815	0.674163	0.858498
LC_6	2.0	0.813624	0.627180	0.855165
LC_{HB2}[1]		0.833879	0.559601	0.849145
LC_1		0.833879	0.559601	0.849145
LC_{11}		0.833879	0.559601	0.849145
LC_{13}		0.833879	0.559601	0.849145
LC_{12}		0.833879	0.559601	0.849145
LC_6	0.5	0.837672	0.512843	0.842085
LC_3		0.748412	0.781225	0.839969
LC_{14}		0.748412	0.781225	0.839969
LC_2		**0.849087**	0.451948	0.832230
LC_9		**0.849087**	0.451948	0.832230
LC_4		0.741493	0.753446	0.805933
LC_{10}		0.551247	**0.962998**	0.730293

Computing accuracy measure is essential because precision and recall (and some other overlap-based measures like F-measure and AUC) do not take into account pixels correctly marked as non-salient, thus methods that fail to detect non-salient regions but perform well on salient ones are favored [17]. Such a case can be observed while applying LC_{10} contrast, which despite good recall performs worse than others in terms of accuracy.

We found that the best performing contrast is LC_7, with the minimum powered by p element-wise as an aggregation function and Reichenbach implication. What is worth noticing, changing the exponent contributes to a trade-off between precision and recall. The same can be observed for another contrast measure (LC_6) with this parameter. Moreover, few definitions contributed by us outperform local contrast specified in [1]. While examining the results one can notice that a couple of measures are equal for a few groups of local contrasts. Such results are obtained in some cases due to the process of image binarization, not the equality of computed saliency maps.

We may observe that recall is relatively low for all contrasts, however, proposed contrast definitions could be used in a preprocessing stage to find possible regions of interests, which could be evaluated by a more accurate, but more computationally complex algorithm.

D. Implementation details and speed-up considerations

Local contrasts measures were implemented in Python programming language, with use of NumPy and scikit-image. As for now, the implementation is directly following given formulas with the use of NumPy vectorization capabilities. Instead of naively evaluating the contrast value for each window there is a possibility to investigate whether histogram-based implementation will give equivalent results with reduced computational complexity. Histogram-based speed-ups are a common technique in image processing and have already been proposed for salient detection [5].

V. Conclusions

In this paper, we provided the construction methods of the local contrast of a fuzzy relation. We focused on the construction method involving the notion of a consensus measure but we also proposed two ways of defining the local contrast with the use of the concept of a similarity measure. The new examples of local contrast were examined in image processing for salient region detection. Few definitions proposed by us outperform local contrast specified by [1] in terms of recall and accuracy.

For future work we plan to develop our work both on theoretical and practical ground. We would like to develop some general construction method involving the concept of the similarity. Moreover, we would like to apply our results in image processing problems.

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References

[1] H. Bustince, E. Barrenechea, J. Fernandez, M. Pagola, J. Montero, C. Guerra, "Contrast of a fuzzy relation", Information Sciences, vol. 180, pp. 1326–1344, 2010.

[2] G. Beliakov, T. Calvo, S. James, "Consensus measures constructed from aggregation functions and fuzzy implications", Information Sciences, vol. 180, pp. 1326–1344, 2010.

[3] L. Itti, C. Koch, and E. Niebur, “A model of saliency-based visual attention for rapid scene analysis", IEEE Trans. Pattern Anal. Mach. Intell., vol. 20, no. 11, pp. 1254–1259, 1998.

[4] R. Achanta, F. Estrada, P. Wils, S. Süsstrunk, "Salient region detection and segmentation, International conference on computer vision systems", Springer, Berlin, Heidelberg, pp. 66–75, 2008.

[5] M. M. Cheng, N. J. Mitra, X. Huang, P. H. S. Torr, and S. M. Hu, “Global contrast based salient region detection", IEEE Trans. Pattern Anal. Mach. Intell., vol. 37, no. 3, pp. 569–582, Mar. 2015.

[6] E.P. Klement, R. Mesiar, E. Pap, "Triangular norms", Kluwer Acad. Publ., Dordrecht, 2000.

[7] M. Baczyński, B. Jayaram, "Fuzzy implications", Studies in Fuzziness and Soft Computing, vol. 231. Springer, Berlin Heidelberg, 2008.

[8] T. Calvo, A. Kolesárová, M. Komorniková, R. Mesiar, "Aggregation operators: properties, classes and construction methods", In: Calvo, T. et al. (eds.) Aggregation Operators, Physica-Verlag, Heidelberg, pp. 3–104, 2002.

[9] D. Gómez, J.T. Rodríguez, J. Montero, H. Bustince, E. Barrenechea, "n-Dimensional overlap functions", Fuzzy Sets Syst., vol. 287, pp. 57–75, 2016.

[10] L. De Miguel, D. Gómez, J.T. Rodríguez, J. Montero, H. Bustince, G.P. Dimuro, J.A. Sanz, "General overlap functions", Fuzzy Sets Syst., vol. 372, pp. 81–96, 2019.

[11] L.A. Zadeh, "Fuzzy sets", Information Contr., vol. 8, pp. 338–353, 1965.

[12] W.J. Tastle, M.J. Wierman, U.R. Dumdum, "Ranking ordinal scales using the consensus measure", Issues in Information Systems, vol. 185, pp. 96–102, 2006.

[13] L. Baccour, A.M. Alimi, R.I. John, "Some Notes on Fuzzy Similarity Measures and Application to Classification of Shapes, Recognition of Arabic Sentences and Mosaic", IAENG International Journal of Computer Science,vol. 41, no. 2, pp. 1–10, 2014.

[14] R. Szeliski, Computer Vision: Algorithms and Applications. Springer-Verlag New York, Inc., 2010.

[15] V. Remeš, M. Haindl, "Region of interest contrast measures", Kybernetika, vol. 54, no. 5, pp. 978–990, 2018

[16] T. Arici, S. Dikbas, and A. Altunbasak, “A histogram modification framework and its application for image contrast enhancement,” IEEE Trans. Image Process., vol. 18, no. 9, pp. 1921–1935, 2009.

[17] A. Borji, M. M. Cheng, Q. Hou, H. Jiang, and J. Li, “Salient object detection: A survey,” Comput. Vis. Media, vol. 5, no. 2, pp. 117–150, Jun. 2019.

[18] M. Carrasco, “Visual attention: The past 25 years,” Vision Res., vol. 51, no. 13, pp. 1484–1525, Jul. 2011.

[19] C. Yang, L. Zhang, H. Lu, X. Ruan, and M. H. Yang, “Saliency detection via graph-based manifold ranking,” in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 3166–3173, 2013.

[20] N. Liu and J. Han, “DHSNet: Deep hierarchical saliency network for salient object detection”, CVPR, pp. 678–686, 2016.

[21] Y.-F. Ma and H.-J. Zhang, “Contrast-based image attention analysis by using fuzzy growing”, in Proceedings of the 11th ACM international conference on Multimedia, pp. 374–381, 2003.