# Wildfire smoke-detection algorithms evaluation

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**Abstract**
*In recent years the interest for terrestrial wildfire smoke detection systems has increased, particularly those based on video systems sensitive in visible and/or infrared (IR) spectra. Although many video based smoke-detection algorithms have been developed and applied in various experimental or real life applications, the standard method for evaluating their quality has not yet been proposed and the standard databases of smoke and no-smoke images and video sequences suitable for standard algorithms testing have not been defined. This paper proposes such a methodology suitable for smoke-detection algorithms testing and evaluation. Various measures for smoke-detection algorithms evaluation have been introduced and a database suitable for off-line algorithms testing is defined. The evaluation is based on notation of observer, the formal theory of perception and signal detection theory. The referent observer (usually the human referent observer) determines the real state of phenomena. In the case of video based smoke detection algorithms, analysed images are considered as a collection of pixels, where each pixel belongs to one of two sets: smoke or no-smoke, and this process of pixel classification is present on both levels: objective level and perceived (or observer) level. Multiple measures based on these two sets are introduced to describe the quality of the observer regarding single image analysis as well as image sequence analysis.*

**Keywords:** smoke detection, wildfire, image processing, detection quality, receiver operating characteristics

## 1. Introduction

Wildfires are a significant hazard to ecological systems around the world and can also be a threat to human safety. Traditional way of fire detection are fire lookout towers located on high grounds with good visibility, where people visually look for signs of fire or smoke appearance. In last ten years wildfire detection systems have been developed to help human observers by alerting them when a smoke-like phenomenon appears.

Such systems are generally conceived of video cameras or other appropriate sensor devices installed on monitoring spots and a computer system that analyses the provided video data and generates potential alarms. Over time these systems have become more and more automated, so one observer can now cover far larger areas than before. Detection algorithms are improved and system capabilities enhanced (Stipaničev *et al.*, 2010). However, as much as it is obvious that these systems have evolved, there are still no standard methods for evaluating such systems and there is no standard image and video database that can be used for testing.

In this paper evaluation methods based on notation of observer, formal theory of perception and signal detection theory are presented as global measures suitable for wildfire detector (in this paper called wildfire observer) overall quality evaluation, but also as local measures suitable for fine tuning different aspects of the observer.

## 2. Notation of observer, formal theory of perception and detection algorithms evaluation

Formal theory of perception introduced by Benett, Hoffman and Prakash (Benett *et al.*, 1989; Benett *et al.*, 1996) defines an observer as a six-tuple:

$$O = (X, Y, E, S, \pi, \eta) \qquad (1)$$

where X and Y are measurable spaces, E and S are subsets of X and Y respectively, $\pi$ is measurable surjective function and $\eta$ conclusion kernel. Space X is a configuration space of the observer and E is a configuration event of the observer. Space X is a formal representation of those possible states of affair over which the configuration event E of the observer is defined. Y is an observation space, or premises space, of the observer. Space Y is a formal representation of the premises available to the observer for making inferences about occurrences of E. S is the observation event. All and only points in S are premises of observer inferences that conclude that an instance of the configuration event E has occurred. $\pi$ is a perspective map, the measurable surjective function from X to Y ($\pi : X \rightarrow Y$) with $\pi(E) = S$. $\eta$ is a conclusion kernel of the observer. For each point in the observation event $s \in S$, $\eta(s,\cdot)$ is a probability measure on E supported on $(\pi^{-1}(s) \cap E)$. This means that kernel $\eta$ is a convenient way of assigning to every point of S a probability measure on E.

In order to achieve perception of the environment and appropriate target phenomenon within that environment sensory input data are needed. Using sensory input as premises, the final decision about the detection of target phenomenon or certain scenario about the environment can be made. Wildfire is taken as a target phenomenon that should be detected by the human observer or automatic detection system. The space X is a set of all possible scenarios that could be encountered in the environment. Some of possible scenarios that could happen are: thunder, lightning, twister, fog and rain. Even a sunny day could be considered as a possible scenario. But only those scenarios or phenomena indicating the occurrence of wildfire are collected in the set E or configuration event that is subset of X. Primary indicator of any event contained in E is presence of smoke and flames, but doesn't necessarily exclude other phenomena, e.g. forest fires are often caused by lightening. Next part is observation space Y, which is highly connected to sensor structure of the system. Observation space is defined as a set that contains all possible sensor states, in relation to all actual possible states of the environment.

The mapping function, or the sensors function is the perspective map $\pi$, which translates every point in configuration space to its pair in observation space. Implementation of the mapping function depends on the sensor itself. If only visual sensors are available then Y will be orthogonal projection of real space that is covered by the camera, if sensors system includes other sensor types, like meteorological sensors then those types of measurements will also be contained in Y. The perspective map has to be surjection, but not necessary injection, so the set Y usually holds fewer elements then set X. Through the process of mapping all the elements in X are mapped to Y and elements belonging to E are mapped to S. So the set S holds those scenarios where the indicators of target phenomenon are collected by the sensors. The structure of wildfire observer is more complex and illustrated in Figure 1. Wildfire observer includes two observer types: the low-level observer and the high-level observer (Stipaničev *et al.*, 2010).

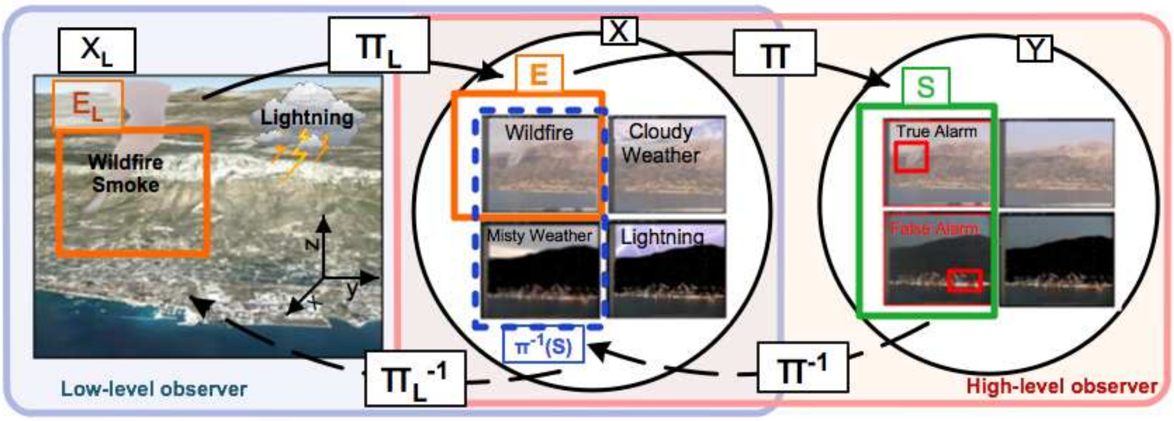



Figure 1. Wildfire observer is composed of low-level observer and high-level observer

The main task of the low-level observer is images acquisition, validation and preparation for the high-level observer whose main task is phenomenon (wildfire smoke) recognition. For further discussion only high-level observer will be considered and we will suppose that only visual sensor is available. In that case the configuration space X of the high-level observer is the set of input images and the observation space Y is the set of output images with detected smoke (observation event S) and without detected smoke. The set E includes all those input images from X where phenomenon (wildfire smoke) is truly present (in practice usually defined by the referent human observer) and the set $\pi^{-1}(S)$ includes input images from X corresponding to images from S where wildfire observer has detected smoke. Figure 2 shows four possible scenarios in detection process: **true detection** or **correct detection** ($x_i \in E$, $y_i \in S$), **false detection** or **false alarm** ($x_i \notin E$, $y_i \in S$), **false not detection** or **missed detection** ($x_i \in E$, $y_i \notin S$) and **true not detection** or **correct reject** ($x_i \notin E$, $y_i \notin S$). In statistical decision theory false alarm is considered as false positive error or type I error and missed detection as a false negative error or type II error and the table in Figure 2 is sometimes called *confusion matrix*.

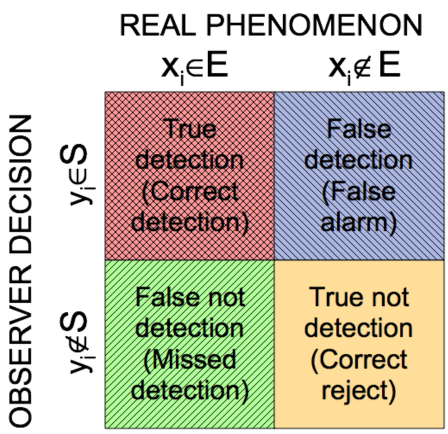



Figure 2. Possible scenarios in wildfire detection

For wildfire observer missed detection is the worst-case scenario because the efficiency of the whole observer is questioned. False detection is the situation where the phenomenon does not exist in reality but the image after detection is mapped in S. It is currently the main problem regarding most commercial wildfire detection systems. Almost every available system has a small number of missed detections, but the number of false detections sometimes could be relatively high.

In order to introduce automatic wildfire observer evaluation measures, first the **referent observer** is introduced. It is a human observer and results of his (her) observations are considered as referent results or ground truth. This method is known as empirical discrepancy method and it is often used in image segmentation evaluation (Zhang, 1996). In the next chapters two types of measures are proposed, **global evaluation measures** suitable for wildfire observer overall quality evaluation (Šerić *et al.*, 2009), and **local evaluation measures** suitable for wildfire smoke-detection algorithms quality evaluation, first time proposed in this paper.

## 3. Global evaluation measures of the wildfire observer

Two types of wildfire detection algorithms could be distinguished, depending on how many input images are used for wildfire detection: a single image wildfire detection and image sequence wildfire detection algorithms. Algorithms belonging to the first case are nothing but special image segmentation algorithms enhanced with recognition of image regions where fire smoke and/or fire flames are presented. In algorithms belonging to the second case, various motion analyses are also applied, so a sequence of input images is needed. Today's wildfire detection algorithms mostly belong to the second case. Usually a short sequence of images, taken every couple of seconds, is used as a unique detection sequence resulting (or not resulting) in one fire alarm.

Global evaluation measures for wildfire smoke detection are based on results regarding both situations where the smallest unit of detection is a single image or a single detection sequence. Wildfire detection in the context of global evaluation is treated as a *binary classification problem*. The task of wildfire observer is to classify the members of the set of input images (or image sequences) into two groups: wildfire present (detected) or wildfire not present (not detected). Wildfire observer classification results (results of wildfire detection process) are then compared with classifications derived from the referent human observer (ground truth).

According to notation of observer and Figure 1, let $X$ be a set of all images (or detection sequences) in a testing collection, $\pi^{-1}(S)$ is a subset of $X$ containing only those images (or detection sequences) where smoke was detected by wildfire observer, and $E$ is a subset of $X$ containing those images which are marked in the ground truth as smoke images where smoke was detected by referent human observer. Individual image (or detection sequences) can be present in both sets, $\pi^{-1}(S)$ and $E$ and that implicates a **correct detection**. A set $TP$ contains those images (or detection sequences) that are correctly detected:

$$TP = \pi^{-1}(S) \cap E \qquad (2)$$

The situation when an image (or detection sequence) is not present in both $\pi^{-1}(S)$ and $E$ is called a **correct reject**. A set $TN$ contains those images (or detection sequences) that are correctly rejected:

$$TN = (\pi^{-1}(S))^C \cap E^C \qquad (3)$$

The situation when an image (or detection sequence) is present in $\pi^{-1}(S)$ and it is not present in $E$ is called a **false alarm**. Set $FP$, is a set of all falsely detected images (or detection sequences):

$$FP = \pi^{-1}(S) \cap E^C \qquad (4)$$

The situations when an image (or detection sequence) is present in $E$ and not in $\pi^{-1}(S)$ is called **missed detections**. Set $FN$ containing all missed detections is defined as:

$$FN = (\pi^{-1}(S))^C \cap E \qquad (5)$$

These situations are illustrated in Figure 3.

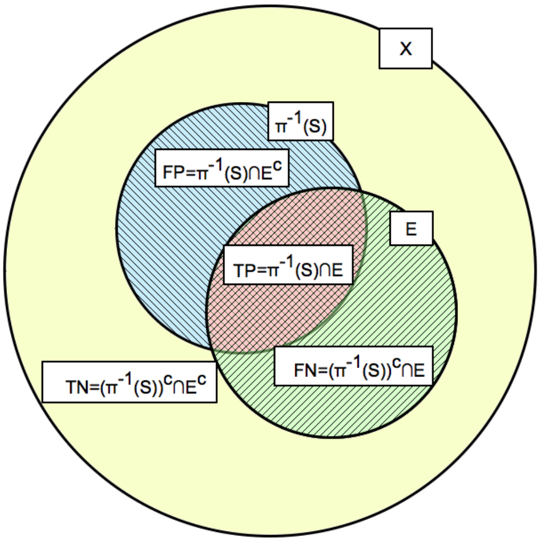



Figure 3. Set theory approach to possible scenarios in wildfire detection

Based on confusion matrix and sets $TP$, $FP$, $FN$ and $TN$, binary classification model defines various measures quite applicable for definition of wildfire observer global evaluation measures. Sensitivity and specificity are maybe the most important of them, especially in connection with receiver operating characteristics (ROC) curves that will be discussed later. **Sensitivity** of the wildfire observer evaluates observer quality according to correct detections (***cd***). It could be defined as true positive rate:

$$cd = TPR = \frac{|TP|}{|E|} = \frac{|TP|}{|TP| + |FN|} \qquad (6)$$

where $|\cdot|$ denotes set cardinality (number of set elements). For example $|TD|$ is the set cardinality of the set $TD$ defined by equation (2) or for wildfire observer it represents the number of images (or image sequences) classified as positively detected (fire alarm generated). Similarly observer quality in the aspect of false detections (***fd***) could be defined as false positive rate:

$$fd = FPR = \frac{|FP|}{|FP| + |TN|} \qquad (7)$$

The observer quality in aspect of correct rejections (***cr***) could be defined as **specificity** or true negative rate:

$$cr = TNR = \frac{|TN|}{|FP| + |TN|} = 1 - FPR \qquad (8)$$

The observer quality in aspect of missed detections (***md***) could be defined as false negative rate:

$$md = FNR = \frac{|FN|}{|TP| + |FN|} = 1 - TPR \qquad (9)$$

All measures take values in interval [0,1]. Figure 3 shows a **real observer** where neither of measure is 1 or 0. *cd* and *cr* have to be as high as possible (or *fd* and *md* as low as possible). Figure 4 shows few special cases. If both measures *cd* and *cr* are equal to 1 (*fd* and *md* are then equal to 0), the observer is declared as an **ideal observer**, at least for testing collection of images or image sequences. This means that all input images or image sequences are correctly classified as smoke or not smoke. Observer is considered a **no-miss observer** if *cd* = 1 (*md* = 0). The good observer has no missed detections and mathematically that implies $E \subset \pi^{-1}(S)$ . Observer is considered a **bad observer** if *cd = 0* (*md* = 1), implying $\pi^{-1}(S) \cap E = \emptyset$. Another extreme case is the **worst observer** when *cd = cr = 0* (*fd = md* = 1), implying $\pi^{-1}(S) = E^C$.

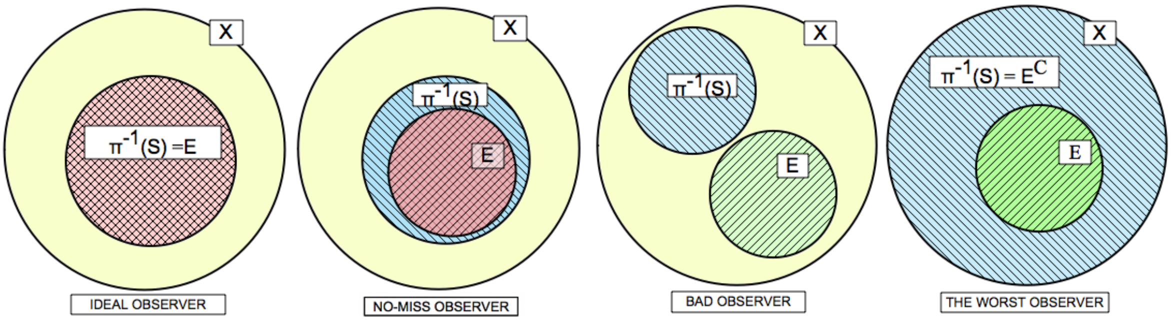
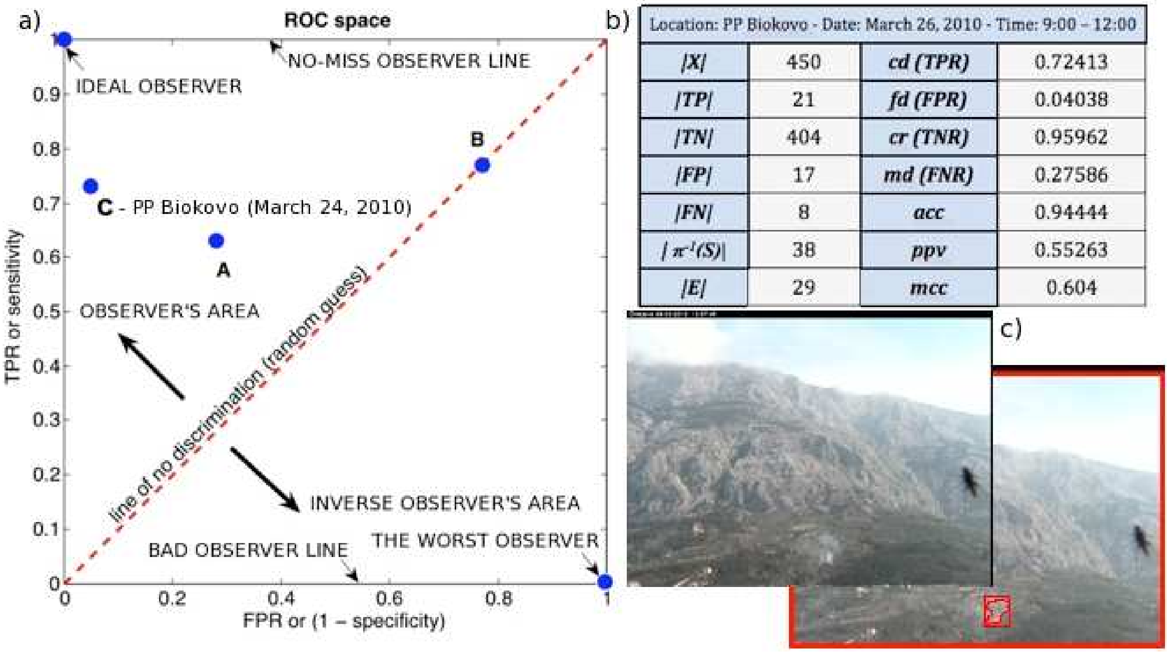



Figure 4. Illustration of various observers according to their quality

Sensitivity and specificity define the ROC (Receiver Operating Characteristics) space, a unit square in coordinate system having (1 – specificity) or false positive rate on x-axis and sensitivity or true positive rate on y-axis. Every analysed wildfire observer could be represented by one point in the ROC space. Figure 5 shows few typical examples. The diagonal divides the ROC space into observer's area and inverse observer's area, because all points bellow the diagonal line could be simply inverted to obtain points above the line. Diagonal correspond to completely random guess which means that if a certain wildfire observer has a corresponding point along the diagonal (for example at point B), the conclusion is that all decisions were made by random or simply flipping coins (head fire, tail non fire). The point (0,1) corresponds to ideal observer and the point (1,0) corresponds to the worst observer. For ideal observer all detections are correct detections and there are no false and missed detections. For the worst observer situation is inversed, all real fires are missed, and all no-fire situations are detected as false detection. Because of that the worst observer could easily become ideal observer by simple decision inversion (when detecting fire conclude not fire and vice versa). The whole line where TPR = 1 is no-miss observer and line with TPR = 0 is bad observer line according to Figure 4. Point (0,0) corresponds to all missed - no false situation and point (1,1) to no missed - all false situation. Points A and

C correspond to two real observers. Observer C is better than observer A, because it has more correct detections and less false detections.




| Location: PP Biokovo - Date: March 26, 2010 - Time: 9:00 – 12:00 | | | |
|---|---|---|---|
| $\|X\|$ | 450 | *cd (TPR)* | 0.72413 |
| $\|TP\|$ | 21 | *fd (FPR)* | 0.04038 |
| $\|TN\|$ | 404 | *cr (TNR)* | 0.95962 |
| $\|FP\|$ | 17 | *md (FNR)* | 0.27586 |
| $\|FN\|$ | 8 | *acc* | 0.94444 |
| $\|\pi^{-1}(S)\|$ | 38 | *ppv* | 0.55263 |
| $\|E\|$ | 29 | *mcc* | 0.604 |

Figure 5. a) The ROC space. b) An example of global evaluation measures calculation. c) An example of missed detection and true detection in the next image sequence.

Few other measures, well known in signal detection theory and error analyses, are also quite suitable for wildfire observer evaluation. The **accuracy** (*acc*) is defined as degree of closeness of measurements of a certain quantity to its actual (true) value (Taylor, 1999). In terms of wildfire observer it could be defined as relation between correctly detected images (or image sequences) and total number of images (or image sequences).

$$acc = \frac{|TP|+|TN|}{|X|} = \frac{|TP|+|TN|}{|TP|+|TN|+|FP|+|FN|} \tag{10}$$

The **positive predictive value** or precision, reproducibility or repeatability (*ppv*) is the degree to which repeated measurements under unchanged conditions show the same results (Taylor, 1999).

$$ppv = \frac{|TP|}{|TP|+|FP|} \tag{11}$$

The **Matthews correlation** (*mcc*) is a quality measure for the binary classification problem (Matthews, 1975). It takes into account true and false positive and negative detections and it is generally regarded as a balanced measure that can be used even if the classes are of very different sizes.

$$mcc = \frac{|TP|\cdot|TN|-|FP|\cdot|FN|}{\sqrt{(|TP|+|FP|)(|TP|+|FN|)(|TN|+|FP|)(|TN|+|FN|)}} \tag{12}$$

An example of global evaluation measures calculation is shown in Figure 5b for iForestFire wildfire monitoring system (Šerić et al., 2009) located in Nature Park Biokovo, Makarska, Croatia. In March 2010 regular annual tuning of detection algorithms were performed based on global evaluation measures. Figure 5a shows an example for March 26, 2010 from 9:00 to 12:00. We have chosen this period because also some missing detections were recorded, but as a meter of fact missing detections were recorded only in the first detection sequence. The system has detected fire successfully in the next detection sequence 2 minutes after the first missed detection.

## 4. Local evaluation measures of the wildfire observer

Local evaluation measures for wildfire smoke detection system are based on results regarding a single image where the smallest unit of detection is one image pixel. Sets $X$, $E$ and $\pi^{-1}(S)$ are now defined as follows: $X$ is a set containing all image pixels, $\pi^{-1}(S)$ is a subset of $X$ containing only those pixels that are marked as smoke by automatic wildfire observer and $E$ is a subset of $X$ containing those pixels that are marked in the ground truth as smoke pixels by referent human observer. Following the methods from the previous chapter the same evaluation measures *cd, fd, cr, md, acc, ppv,* and *mcc* could be defined, but this time on the local image level.

To illustrate the application of the global and local evaluation measures a collection of 6 different image sequences were used, having all together 256 images with time difference of 1 second. On 5 sequences the wildfire smoke was present, and 1 sequence was without the smoke. These image sequences are part of our standard wildfire smoke video database used for testing various smoke detection algorithms (SmokeRec, 2010). As a smoke detection algorithm method described by (Toreyin *et al.*, 2006) has been used. Figure 6 shows one typical image from image collection and Figure 7 shows average results of global and local measures calculation.

Figure 6. Typical image from image collections used in algorithm evaluation (input image, ground true image segmentation, and detection result)

| 6 image sequences | | 256 images | | 113 246 208 pixels | |
|---|---|---|---|---|---|
| *cd (TPR)* | 1 | *cd (TPR)* | 0.5055 | *cd (TPR)* | 0.19 |
| *fd (FPR)* | 0 | *fd (FPR)* | 0.0038 | *fd (FPR)* | $1.06 \times 10^{-4}$ |
| *cr (TNR)* | 1 | *cr (TNR)* | 0.9877 | *cr (TNR)* | 0.9999 |
| *md (FNR)* | 0 | *md (FNR)* | 0.4945 | *md (FNR)* | 0.81 |
| *acc* | 1 | *acc* | 0.6602 | *acc* | 0.9939 |
| *ppv* | 1 | *ppv* | 0.9888 | *ppv* | 0.87 |
| *mcc* | 1 | *mcc* | 0.4834 | *mcc* | 0.18 |

Figure 7. Global and local evaluation measures for 256 images in 6 image sequences

The first group of rows in Figure 7 shows global measures concerning image sequences, the second one shows global measures concerning all images in all image sequences and the third group shows local measures concerning all pixels in all images. Figure 7 shows that the same algorithm behaved as an ideal observer on image sequence level and as a real observer on image collection level and on image pixels level. On image sequence level smoke has been detected in all 5 image sequences, but on image collection and image pixels level the algorithm has detected smoke after approximately 20 images and that is the reason why there are a lot of missed detections (measure *md* high).

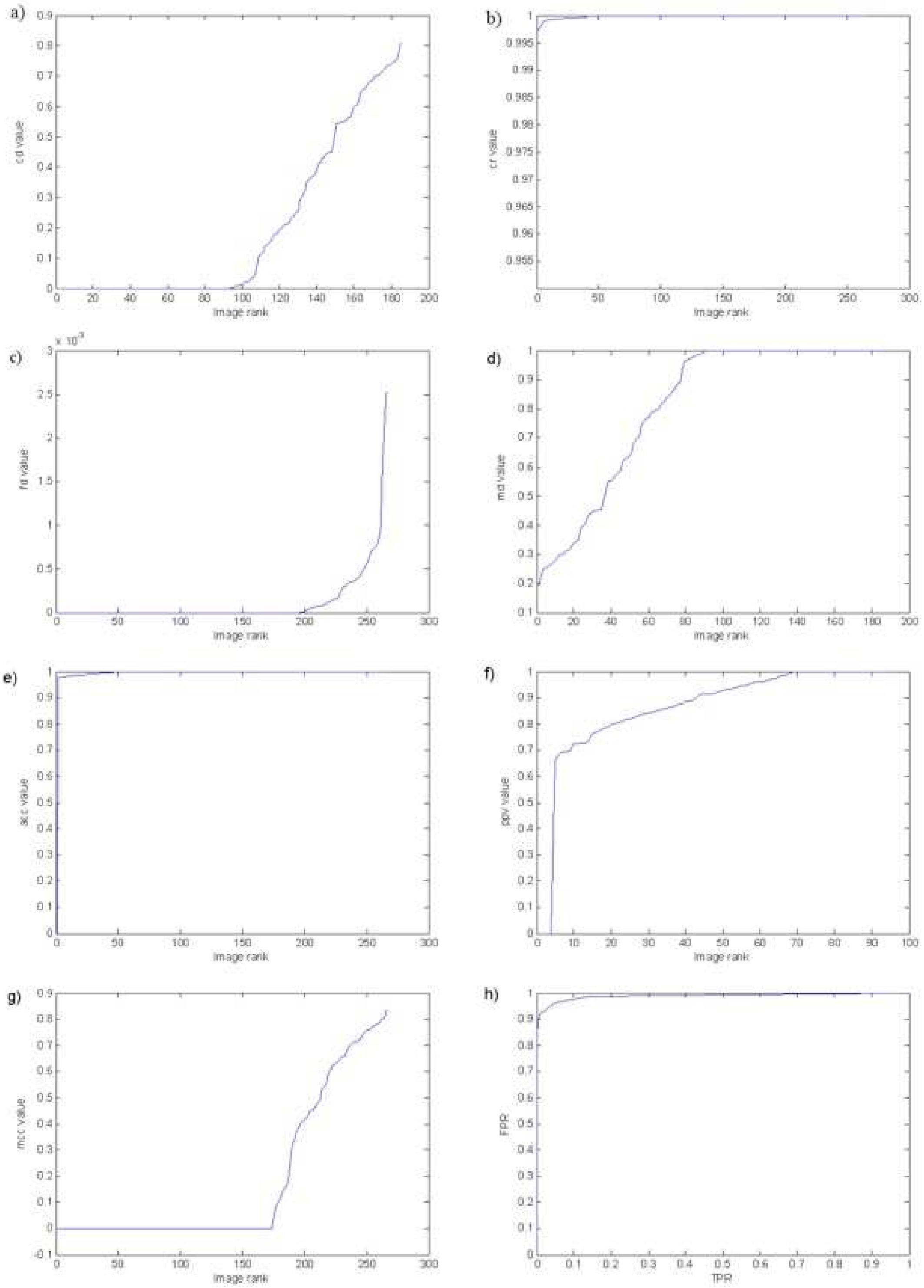



Figure 8. Quality graphs: a) *cd*, b) *cr*, c) *fd*, d) *md*, e) *acc*, f) *ppv*, g) *mcc and h) ROC curve*

Beside these average measures in this paper we would like to propose the **observer quality graphs** as a more useful tool for smoke detection algorithms evaluation. Observer quality graph is a graph showing values of the specific measure for all the images in the collection sorted increasingly according to measure values. Figures 8 shows observer quality graphs for measures *cd, cr, fd, md, acc, ppv,* and *mcc*.

Algorithm evaluation on local scale can also be performed using *ROC* (Receiver Operating Characteristics) curves. *ROC* curve is a graph in *ROC* coordinate system shown in Figure 5a obtained by plotting the trade-off for every possible detection algorithm threshold (Fogarty *et al.*, 2005). The tradeoffs at different thresholds between obtaining more true positives at the expense of additional false positives detections for analysed detection algorithm is shown Figure 8h. *ROC* curve is usually plotted for a single image using multiple thresholds. Although the curve is plotted with different thresholds it cannot be taken as an absolute criterion for classifier evaluation because the curve is specific for each image. Different conditions present at the detection site generate different curves; however it can be used as a general indicator of classifier performance.

## 5. Fuzzy local evaluation measures for wildfire observer

Wildfire smoke is by its nature an amorphous phenomenon without exact borders and edges. When observed from a small distance it is a semi-transparent phenomenon that gradually occludes the background. Smoke detection is quite difficult task because of its transparency and undefined shape and because of that the smoke detection systems are prone to missed and false detections. When evaluating different smoke detection methods pixels on the image categorised by referent human observer are often categorised as binary categories: smoke or non-smoke (smoke background). This approach can lead to a precision error in evaluation because the transparency of the smoke can make the pixel partially smoke, and partially background. Figure 8. illustrates that smoke boundaries cannot be precisely defined, certain pixels can clearly be categorised as smoke, and others are much more difficult to distinguish from the background.

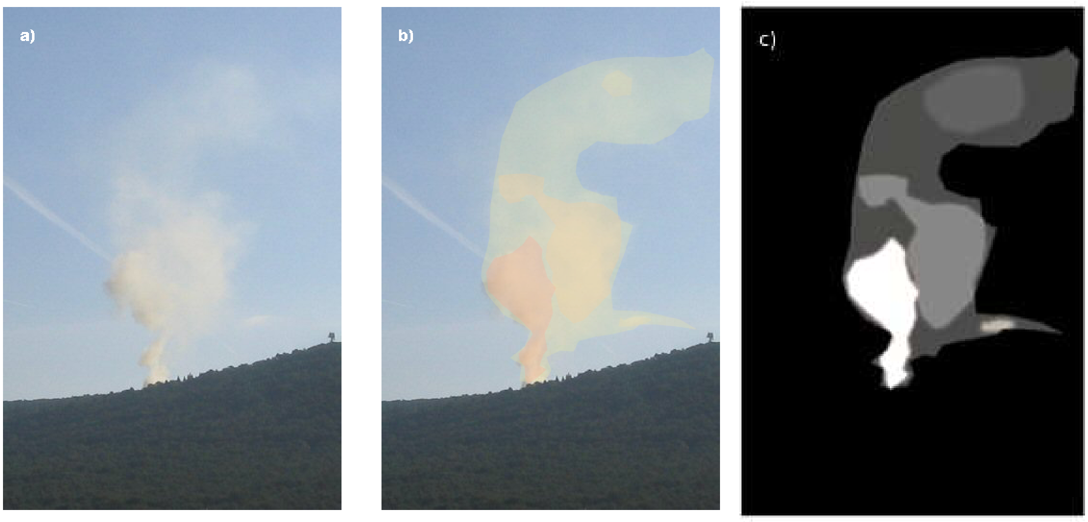



Figure 8. a) Original image, b) image overlaid with pixel membership to class *smoke* in colour space and c) ground true fuzzy segmentation

In order to reduce the evaluation error a new method for smoke-detection algorithm evaluation based on fuzzy logic is presented. Every pixel in the image can have a degree of membership to the class *smoke* as well a degree of membership to the class *background*. The membership degree for each class can be hard to determine precisely even for a human observer, but it can be estimated within a reasonable level of certainty. The degree of membership can have a value from the interval [0,1] where 1 indicates the pixel most definitely belongs to certain class (in our case smoke). The relation between memberships of classes *smoke* and *smoke background* could be defined as

$$\mu_b(x) = 1 - \mu_s(x) \tag{13}$$

where $\mu_b(x)$ is a background membership function for the pixel $x$ and $\mu_s(x)$ is a smoke membership function for the pixel $x$. Most current detection algorithm can be modified to generate fuzzy output in form of probability of image pixels belonging to a certain class and such output is compared to referent ground-truth fuzzy-segmented images. Evaluation is used to determine the real error of the algorithm taken into consideration the conditions and the error cost. Error in which a false alarm is generated has a lot lower cost than error in which the smoke is not detected and in accordance with such criterion evaluation of the detection algorithm is performed. Let us first introduce the error $err_p$ for a pixel $p$ calculated using equation:

$$err_p(R,O) = \begin{cases} 3 \cdot R \cdot (R - O) & R > 0 \\ O - R & O \geq R \end{cases} \tag{14}$$

where $R$ is the referent fuzzy value for the pixel $p$ and $O$ is the fuzzy value given by the observer (algorithm) for the same pixel. This measure takes into account the type of error as well as the extent of the error. For $O > R$ the assessed value for the smoke membership is grater then in the referent ground-truth fuzzy-segmentation. This scenario is called **fuzzy false detection** and its cost is much less then for scenario called **fuzzy missed detection** when $R > O$. The error cost for fuzzy missed detection increases with referent fuzzy value for the pixel $p$ and with the difference between observer and referent values. Special case is $O = R$ when the error value is zero $err_p(R,O) = 0$. Let us now introduce measure $ng_S$ for smoke detection algorithms evaluation on one image level as average error of the whole image:

$$ng_S = \frac{1}{P} \sum_p err_p(R,O) \tag{15}$$

where $P$ is the total number of pixels in analysed image. This measure has to be as low as possible. For example for smoke detection algorithm analysed in previous chapter and a collection of 6 image sequences having 256 images average $ng_S$ measure was 6.48.

## 6. Conclusion

Smoke detection has bas been a field of active research in the last ten years. Significant number of smoke detection systems has been developed; however, there is no standard way of testing the performance of the complete system. In this paper various methods for smoke-detection evaluation based on the notation of observer, formal theory of perception and signal detection theory have been presented. Evaluation measures are proposed as global evaluation measures and local evaluation measures depending on the aspect of the classifier being evaluated. The transparent property of the smoke is also taken into account using fuzzy-based evaluation. Average fuzzy error could be computed using referent fuzzy-segmentation compared against algorithm output on the pixel-bases. Proposed measures could be used as a tool for smoke-detection algorithm evaluation, either for comparison of different algorithms or for individual algorithms fine-tuning in order to achieve better performances.

## 7. Acknowledgement

This work was partly supported by the Ministry of Science, Education and Sport of Republic Croatia under Grants TP-03/0023-09 "System for early forest fire detection based on cameras in visible spectra" and 023- 0232005-2003 "AgISEco - Agent-based intelligent environmental monitoring and protection systems", and Split and Dalmatia County authorities through a study „Holistic approach to forest fire protection in Split and Dalmatia County“.

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