The detection of moving objects in video by background subtraction using Dempster-Shafer theory

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Abstract – Detection of moving objects has been widely used in many computer vision applications like video surveillance, multimedia applications, optical motion capture and video object segmentation. The key steps in detecting the moving objects are the background subtraction and the foreground detection. To handle these processes, we need to classify the corresponding pixels of the current image as background or foreground. This paper describes the background subtraction and the foreground detection within the context of Dempster-Shafer theory which better represents uncertainty by considering the situations of risk and ignorance. The proposed method addresses the methodology modeling in the Dempster-Shafer theory of evidence by representing the information extracted from the current image as measures of belief. The mass functions are computed from the probabilities assigned to each class being combined with the Dempster-Shafer rule of combination and the maximum of mass function is used for decision-making. The proposed method has been tested on several datasets showing an optimal performance compared to other fuzzy approaches based on the Sugeno and Choquet integrals and has proved its robustness.

Keywords: Dempster-Shafer theory of evidence, background subtraction, foreground detection, uncertainty information, data fusion, decision.

I. INTRODUCTION

Background subtraction techniques have been used in many applications in which the background is not static, for instance in video surveillance [1], multimedia applications [2], optical motion capture [3], video object segmentation [4]. These techniques are based on different methods for subtracting the background and properly manage the background modeling, thus several surveys can be found in [5][6][7].

The basic operation needed is the separation of the moving objects called "foreground" from the static information known as "background" [5]. Background subtraction is the particular case when: 1) one image is the background image and the other one is the current image, and 2) the changes are due to moving objects. Therefore, in this paper we focus on the detection of moving objects in videos. The idea of background subtraction is to find the difference between the current image and the corresponding reference of the background model. Such comparison is made by using color and texture features to compute similarity measures between pixels in current and background images.

The main contribution of this paper is to propose a foreground-background segmentation algorithm using a Dempster-Shafer fusion approach. Each pixel is characterized by its mass functions defining each corresponding classes. The final segmentation is carried by assigning each pixel to the maximum belief assumption of its corresponding class. This paper is organised as follows. In Section II we present some researches that have shown an important impact into the background subtraction area and some recent surveys regarding Dempster-Shafer applicability in image segmentation. Section III highlights a brief review about background subtraction techniques and some fundamental concepts regarding Dempster-Shafer theory of evidence are described in Section IV. Furthermore, the description of our system is illustrated in Section V and in Section VI we discuss the similarity measures. A brief explanation of our proposed Dempster-Shafer method is given in Section VII followed by the experiments in Section VIII. Based on the results obtained, we highlight some relevant conclusions and future improvements in Section IX.

II. RELATED WORK

Many researches about background subtraction can be found in the literature [5][8][9]. In [5], Bouwmans highlighted a complete overview of the concepts, theories, algorithms and applications regarding both traditional and recent approaches in background modeling for detecting the foreground. As image segmentation can be made using fuzzy foreground detection, Zhang and Xu [10] used texture and color features to compute similarity measures between current and background pixels. These similarity measures have been aggregated by applying the

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Sugeno integral. The moving objects are detected by thresholding the results of the Sugeno integral. El Baf et al. [11] used the same features but applying the Choquet integral instead of the Sugeno approach proving robustness to shadows and illumination changes. Recently, Azab et al. [12] have aggregated three features, that are color, edge and texture. Fuzzy foreground detection is more robust to illumination changes and shadows than crisp foreground detection. There are available several background-foreground segmentation algorithms, as for example the Background Subtraction Library (BGSLibrary) developed by Sobral [13] which provides a C++ framework including statistical models, clustering models, neural networks and fuzzy models.

The use of Dempster-Shafer theory of evidence has shown relevant challenges in many applications [14][15][16], and also in the image segmentation area [17][18]. Moro et al. [19] introduced an improved foreground-background segmentation algorithm using the Dempster-Shafer theory by providing significant improvements in a complex scenario. Their approach performs successfully the background modeling for moving objects that remain stationary for a long time and start moving again. The Dempster-Shafer theory has been also used in skin detection researches [20] as a powerful and flexible framework for representing and handling uncertainties in available information and overcome the limitations of the current state-of-the-art methods.

In this paper, we seek to perform the Dempster-Shafer fusion approach in detecting the foreground by aggregating both color and texture features. The aim is to prove if our proposed method can perform better than the already applied Sugeno and Choquet fuzzy integrals.

III. BACKGROUND SUBTRACTION: A BRIEF REVIEW

Several background subtraction methods have been discussed in many articles proving their efficiency along their corresponding implementation [13]. The simplest way of modeling the background is to consider a background image without any moving object. Moreover, the background can be affected by critical changes such as illumination changes, dynamic backgrounds, objects being introduced or removed from the scene [5]. To overcome these issues, the background representation model must be robust and adaptive.

There are various background representation models that were developed along the time, from the traditional to the recent ones such as:

• *Basic Background Modeling:* The basic way of modeling the background is by either using the average [21], median [22] or histogram analysis over time [23]. Once the model is computed, the foreground detection can be determined as follows:

$$d(I_t(x, y) - B_{t-1}(x, y)) > T \qquad (1)$$

where T is a constant threshold, $I_t(x, y)$ the current image and $B_t(x, y)$ the background image at time t. If condition 1 is not accomplished, the pixels are assigned as background.

• *Statistical Background Modeling:* The background representation is modeled using a single Gaussian [24], a Mixture of Gaussians [25][26][27] or a Kernel Density Estimation [28][29][30]. Statistical models are used in detecting pixels as background or foreground due to their robustness to illumination changes and dynamic backgrounds.

• *Fuzzy Models:* These models take into consideration the imprecisions and the uncertainties encountered in the process of background subtraction. The algorithm commonly used is the Gaussian Mixture Model [31], but one drawback is that the parameters are determined using a training sequence which might contain insufficient or noisy data. Combining approaches consisting of aggregating different features such as color and texture lead to robust results. Therefore, El Baf et al. [11] have fused these two features using the Sugeno and Choquet aggregation integrals proving that using more than one feature can better overcome the illumination changes and shadows issues.

As seen previously, a large variaty of background representation models can be used depending on the critical situations that need to be handled.

IV. DEMPSTER-SHAFER THEORY OF EVIDENCE: SOME FUNDAMENTALS

The Dempster-Shafer (D-S) theory of evidence was introduced by Dempster [32] and Shafer [33]. It provides a unifying framework for representing uncertainty by taking into consideration the situations of risk and ignorance. The D-S theory of evidence can be interpreted as a generalization of probability theory where probabilities are assigned to sets of possible events.

In this framework, each information i is characterized by a mass function m_i that can be mapped into the numerical values interval [0, 1] to each subset of the discernment set Ω. D-S allows the representation of both imprecision and uncertainty through the definition of two functions: *belief* (Bel) and *plausibility* (Pl), both derived from a mass function m [34][32].

Considering the set of classes of interest:

$$\Omega = \{C_1, C_2, ..., C_i\} \qquad (2)$$

The mass function m represents the function from 2^{Ω} onto [0, 1], such that:

$$m : 2^{\Omega} \rightarrow [0, 1] \qquad (3)$$

$$m(\emptyset) = 0, \quad \sum_{A \subset \Omega} m(A) = 1 \qquad (4)$$

A subset *A* with non-zero mass value is called a focal element. As explained above, belief and plausibility functions are derived from the mass functions. The Belief function for a set *A* is defined as the sum of all the basic probability assignments of the proper subsets (*B*) of the set of interest (*A*) (see equation 5). The Plausibility represents the sum of all the basic probability assignments of the sets (*B*) that intersect the set of interest (*A*) (see equation 6). The belief and plausibility functions satisfy the condition shown in equation 7.

$$Bel(A) = \sum_{B \subseteq A} m(B) \qquad (5)$$

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B) \qquad (6)$$

$$Bel(A) \leq Pl(A) \qquad (7)$$

The combination rule is generated by the orthogonal sum expressed for *n* sources as:

$$\oplus_{i=1}^{n} m_i(A) = \frac{1}{1-K} \sum_{B_1 \cap B_2 \cap \ldots \cap B_n = A} m_1(B_1)\ldots m_n(B_n) \qquad (8)$$

where *A*, B_1, B_2, ..., B_n are the subsets of Ω and *K* is the basic probability mass associated with conflict determined by summing the products of the mass functions of all sets where the intersection is null (see equation 9).

$$K = \sum_{B_1 \cap B_2 \cap \ldots \cap B_n = \emptyset} m_1(B_1) \ldots m_n(B_n) \qquad (9)$$

The denominator in Dempster's combination rule, *1−K* is a normalization factor that attributes any probability mass associated with conflict to the null set so as to ignore the conflict [33].
Note that the combination rule is commutative, associative, but not idempotent or continuous.

V. SYSTEM OVERVIEW

The first step of several video analysis systems is represented by the segmentation of foreground objects from the background. This task is very important since the background subtraction algorithm has to cope with a number of critical situations (e.g., presence of noise, continuous and sudden illumination changes, permanent and temporal variation in background objects).
In the following subsections, we briefly discuss the fundamental steps that were taken into consideration when building our system.

A. Background subtraction

The main steps in detecting the background are illustrated in Fig. 1.
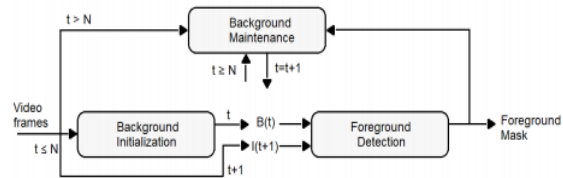

Fig. 1: Diagram of the background management.

a. Background initialization

This first step requires an important attention of exploiting the frames at the beginning of the sequence. In our case, the background initialization is made by using the average of the N first video frames where objects were present.

b. Background maintenance

An update rule of the background model is required in order to adapt its changes occured in the scene over time. The selective maintenance scheme used is:

$$B_{t+1}(x, y) = (1-\alpha)B_t(x, y) + \alpha I_{t+1}(x, y)$$
$$\textit{if} \quad \textit{(x,y)} \quad \textit{is} \quad \textit{background} \qquad (10)$$
$$B_{t+1}(x, y) = (1-\beta)B_t(x, y) + \beta I_{t+1}(x, y)$$
$$\textit{if} \quad \textit{(x,y)} \quad \textit{is} \quad \textit{foreground} \qquad (11)$$

where $B_t(x, y)$ is the background image, $I_{t+1}(x, y)$ is the current image, α is the learning rate which determines the speed of the adaptions to illumination changes and β is the learning rate which handles the incorporation of motionless foreground objects.

c. Foreground detection

This step represents a classification task and consists of labeling pixels as background or foreground. Our foreground detection process is shown in Fig. 2. First, we extract color and texture features from the background image *B(t)* and the current image *I(t + 1)*. Furthermore, the similarity measures are computed for each feature and then they are aggregated by Dempster-Shafer method. Finally, the classification of background/foreground is made by thresholding with the D-S maximum belief assumption.
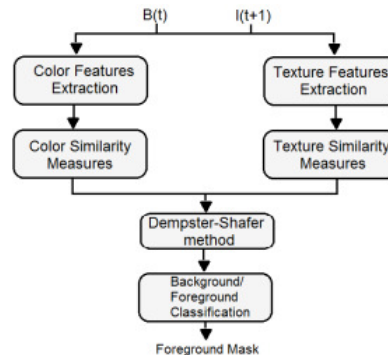

Fig. 2: Foreground detection process.

B. Color and texture features

The choice of features is an important task due to their different properties which allow to handle the critical situations differently. Color features are often very discriminative but they have several limitations in the presence of illumination changes, camouflage and shadows. Texture is adapted to the illumination changes and shadows. The addition of several features together can lead to even more robust results.

a. Color features

A number of color space comparisons are presented in the literature [35][36]. In foreground detection, the most commonly used color space is RGB due to being directly available from the sensor or the camera.
For building our system, we use the RGB color space. We choose two components according to the relevant information which they contain so as to have the least sensitivity to illumination changes.

b. Texture feature

We use the eXtended CS-LBP (XCS-LBP) texture feature which was developed by Silva et al. [37]. This texture feature extracts image details by comparing the gray values of pairs of center-symmetric pixels and considering the result as a binary number.
The XCS-LBP mathematical expression is:

$$XCS - LBP_{P,R}(c) = \sum_{i=0}^{(P/2)-1} s(g_1(i,c) + g_2(i,c))2^i \quad (12)$$

where $g_1(i,c)$ and $g_2(i,c)$ are considered as:

$$\begin{cases} g_1(i,c) = (g_i - g_{i+(P/2)}) + g_c \\ g_2(i,c) = (g_i - g_c)(g_{i+(P/2)} - g_c) \end{cases} \quad (13)$$

and the threshold function s which determines the types of local pattern transition is defined as follows:

$$s(x_1 + x_2) = \begin{cases} 1, & if \quad (x_1 + x_2) \geq 0 \\ 0, & otherwise. \end{cases} \quad (14)$$

Therefore, we perform the fusion of these two features, namely color and texture, by using the Dempster-Shafer theory which will be described in section VII.

VI. SIMILARITY MEASURES

Foreground detection is based on the comparison between the current and the background images. We propose to detect the foreground by defining a similarity measure between pixels in the current and background images.

A. Color similarity measures

When computing the color similarity measure, we consider:

$$S_k^C(x,y) = \begin{cases} \dfrac{I_k^C(x,y)}{I_k^B(x,y)}, & if \quad I_k^C(x,y) < I_k^B(x,y) \\ 1, & if \quad I_k^C(x,y) = I_k^B(x,y) \\ \dfrac{I_k^B(x,y)}{I_k^C(x,y)}, & if \quad I_k^C(x,y) > I_k^B(x,y) \end{cases} \quad (15)$$

where $k \in \{1, 2, 3\}$ is one of the three color features, B and C is the background and the current images at time t. If $I_k^B(x,y)$ and $I_k^C(x,y)$ are similar, we assign 1 as value, otherwise the values correspond between 0 and 1.

B. Texture similarity measures

Based on the same idea, the texture similarity measure $S^T(x, y)$ for the pixel (x, y) is computed as follows:

$$S^T(x,y) = \begin{cases} \dfrac{L^C(x,y)}{L^B(x,y)}, & if \quad L^C(x,y) < L^B(x,y) \\ 1, & if \quad L^C(x,y) = L^B(x,y) \\ \dfrac{L^B(x,y)}{L^C(x,y)}, & if \quad L^C(x,y) > L^B(x,y) \end{cases} \quad (16)$$

where $L^B(x,y)$ and $L^C(x,y)$ represent the texture of pixel (x,y) of the background and the current images at time t. $S^T(x,y)$ is 1 if $L^B(x,y)$ and $L^C(x,y)$ are similar, otherwise $S^T(x,y)$ is assigned between 0 and 1.

VII. THE PROPOSED DEMPSTER-SHAFER ALGORITHM

Another fundamental task in foreground detection is the aggregation of the similarity measures through Dempster-Shafer theory. Starting from the theoretical concepts discussed in section IV, we propose the following problem formulation:
Let us consider the discernment set comprising three main classes, that are FG representing the foreground, BG the background, Θ the uncertainty and $m(\emptyset) = 0$ (see equation 17).

$$\Omega = \{\emptyset, FG, BG, \Theta\} \quad (17)$$

A suggestive framework describing the Dempster-Shafer fusion's flow is illustrated in Fig. 3.
For each pixel (x,y), we take into consideration three sources represented by the two color components of the RGB color space and the XCS-LBP texture feature. For each source, we define three hypothetical mass functions corresponding to the foreground, background and uncertainty classes.
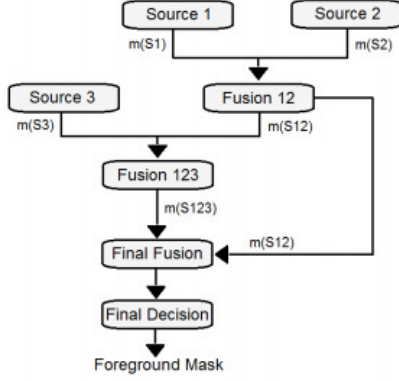
Fig. 3: Dempster-Shafer fusion's framework.

We start fusing the first two sources (e.g., the two color components) by using all the corresponding probabilities assigned to each of the class.

For instance, when fusing R and G components we calculate the combination rule for each class as follows:

$$m(S12)_{FG} = m_{FGR}m_{FGG} + m_{FGR}m_{\Theta G} + m_{FGG}m_{\Theta R}$$
$$m(S12)_{BG} = m_{BGR}m_{BGG} + m_{BGR}m_{\Theta G} + m_{BGG}m_{\Theta R}$$
$$m(S12)_{\Theta} = m_{\Theta R}m_{\Theta G} \qquad (18)$$

where the factor of conflict, K, is defined as:

$$K = m_{FGR}m_{BGG} + m_{BGR}m_{FGG} \qquad (19)$$

Then, we determine the next fusion between the third source $m(S3)$ and the previous fusion result $m(S12)$.

The final fusion is represented by the sum of the two fused results normalized so that to assign the values in the [0, 1] interval. We can now define the [Belief, Plausibility] interval which is computed as follows:

$$Bel = M_{FG}$$
$$Pl = M_{FG} + M_{\Theta}$$
$$Bel \leq Pl \qquad (20)$$

where M_{FG} and M_{Θ} are the results of the final fusion describing the foreground and the uncertainty.

After knowing both Belief and Plausibility, we search for the best decision rule by determining which of the hypotheses mass functions are included in the interval assigning the foreground as following:

$$\begin{cases} m(S1) + m(S2) + m(S3) \leq \max(Bel) \\ pixel \ (x,y) \ is \ foreground \\ otherwise, \\ pixel \ (x,y) \ is \ background \end{cases} \qquad (21)$$

After all these steps, we can proceed in extracting the foreground mask and the obtained results are shown in the following section.

VIII. EXPERIMENTS

The proposed Dempster-Shafer method has been evaluated with several datasets: the first one is the Aquateque dataset[3] used in a multimedia application [2] where the output images are 384×288 pixels, and the second dataset[4] provided for the Scene Background Modeling and Initialization (SBMI2015) workshop. For each dataset, we provide a comparison with other approaches such as Sugeno and Choquet fuzzy integrals [11] where their threshold is optimized to give the best results.

A. Aquateque dataset

This dataset consists of video sequences presenting fishes in tank. The goal is to detect the fishes and identify them. In these video sequences, there are several critical local or global situations such as the illumination changes owed to the ambient light, the spotlights which light the tank from the inside and from the outside, the movement of the water due to fish and the continuous renewal of water. Furthermore, the aquarium environment (e.g., rocks, algae) and the texture of fishes amplify the consequences of the brilliant variations.

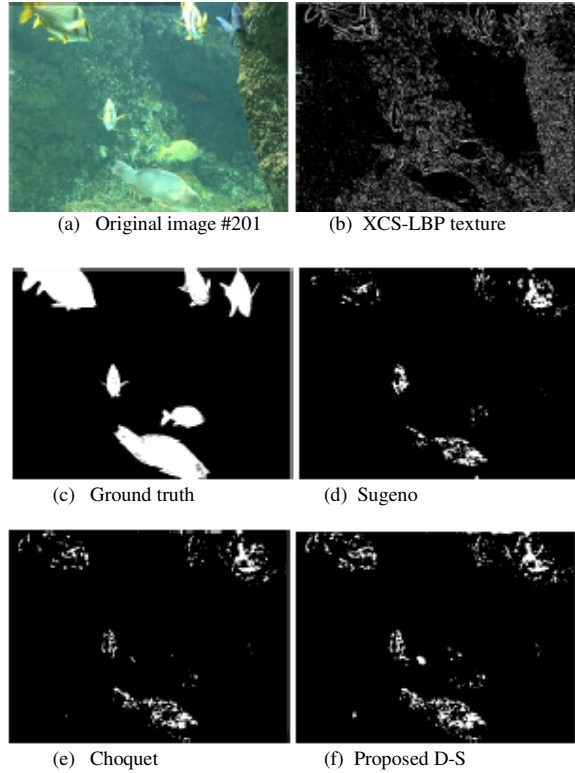Fig. 4 illustrates the experiments performed on the sequence #201.

(a) Original image #201   (b) XCS-LBP texture

(c) Ground truth   (d) Sugeno

(e) Choquet   (f) Proposed D-S

Fig. 4: Aquateque dataset.

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[3] sites.google.com/site/thierrybouwmans/recherche---aqu-theque-dataset
[4] sbmi2015.na.icar.cnr.it

As shown above, we expose the ideal result given by the ground truth (see 4c) with the results obtained by applying the two existing approaches (see 4d and 4e) and our proposed Dempster-Shafer method (see 4f). As can be observed, the proposed method gives more optimal results than the other two approaches.

Furthermore, we compute the quantitative evaluation using the similarity measure performed also in [11]. Considering *A* being a detected region and *B* the corresponding ground truth, the similarity measure between *A* and *B* can be defined as:

$$S(A,B) = \frac{A \cap B}{A \cup B} \qquad (22)$$

If *A* and *B* are similar, *S(A,B)* approaches 1, otherwise 0. Table 1 shows the similarity values obtained when applying the three methods over the sequence #201 of the Aquateque dataset. As can be seen, the best result is given by our proposed method, thus foreground pixels have been better mapped by performing D-S method than the other two approaches.

Table 1: Similarity Measure

Method	Sugeno	Choquet	D-S
S(A,B)	0.166	0.159	0.205

To further estimate the performance of each algorithm, we show in Table 2 the results obtained regarding *Precision*, *Recall* and *F-measure*. In order to do that, we compute each of the measures as follows:

$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{TP + FN}$$
$$F - measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \qquad (23)$$

where *TP* is the total number of true positives, *FP* the total number of false positives and *FN* the total number of false negatives.

As F-measure is assigned within the [0, 1] interval, the higher the F-measure the better performance of the algorithm on detecting correctly the pixels as foreground. Therefore, we can notice that our proposed method gives the optimal results compared to the Sugeno and Choquet integrals.

Table 2: Performance Measures

Method	Sugeno	Choquet	D-S
Precision	0.811	0.816	0.799
Recall	0.173	0.164	0.216
F-measure	0.285	0.274	0.340

B. SBMI2015 datasets

Furthermore, we test our proposed Dempster-Shafer method on another datasets provided by SBMI2015. These datasets consists of indoor and outdoor sequences in video surveillance context. The goal is to detect moving persons and/or vehicles. We also provide the comparison of our proposed algorithm with respect to the Sugeno and Choquet approaches. Once again, we illustrate that the use of our proposed method gives more robustness in the foreground-detection segmentation.
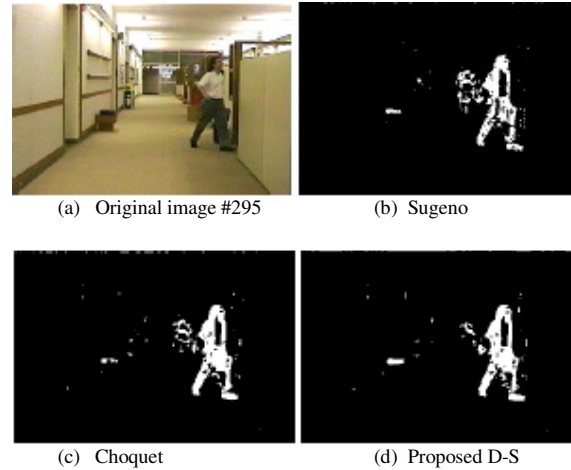

(a) Original image #295 (b) Sugeno

(c) Choquet (d) Proposed D-S

Fig. 5: Hall&Monitor dataset.

(a) Original image #257 (b) Sugeno

(c) Choquet (d) Proposed D-S

Fig. 6: CaVignal dataset.
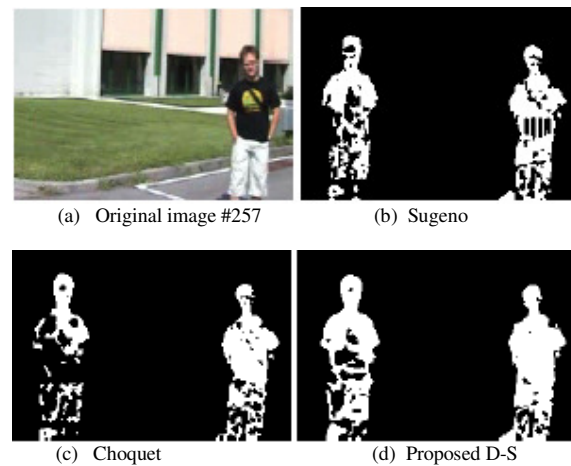

(a) Original image #499 (b) Sugeno
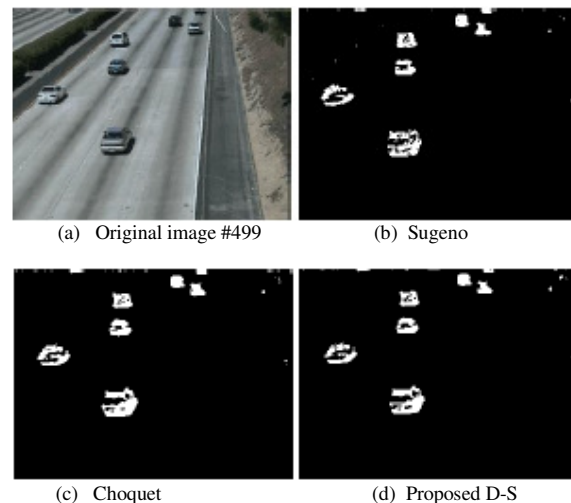
(c) Choquet (d) Proposed D-S

Fig. 7: HighwayII dataset.

IX CONCLUSION

In this paper, we have presented a foreground detection method using the Dempster-Shafer fusion approach for aggregating RGB color space and XCS-LBP texture features. The experiments using Aquateque and SBMI2015 datasets show more robustness to shadows and illumination changes than the other two methods. Furthermore, the quantitative evaluation reflects that our proposed method gives better results than the use of the Choquet and Sugeno fuzzy integrals.

Some directions of the future work include the expansion of the fusion and comparison of other color and texture features. Another further research consists of performing more quantitative evaluations on other datasets proving the Dempster-Shafer method's efficiency.

ACKNOWLEDGEMENTS

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