Insects detection in maize by endoscopic video analysis

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Abstract— *Insects cause significant quantity and quality losses in stored grains. Producers are recommended to avoid excessive use of insecticides because they are harmful to living beings that consume the grains. Thus, it is of vital importance to early identify insects in grains to take control measures. Insects identification is usually done by collecting samples of grains from warehouses, followed by visual or laboratory analysis. However, this is a difficult and costly process. We propose to carry out this identification task automatically, using computational methods to perform endoscopic video analysis. The videos are recorded inside of grains warehouses by a endoscopic camera. As the classification process of moving objects in video depends fundamentally on precise segmentation of moving objets, we propose a new method of background subtraction and compared their results with the main methods of the literature according to a recent review. Experimental results show that the proposed method achieve more accurate results than state of art methods.*

Keywords: Background Subtraction, Segmentation, Video Analysis, Classification

1. Introduction

The growing need for food to meet the global demand, increased by the population growth, requires the grains harvested to be maintained with minimal losses to final consumption. However, stored grains are highly susceptible to insects infestation. Elias et. al (2008) in [8] reports that currently has several types of grain storages available in Brazil, but in all are susceptible to insects infestation. As intensive use of insecticides discouraged because they are harmful for living beings that manage and consume the grains, a timely identification of insects in the grains is of great importance to take measures to avoid losses. Yet according to [8], in Brazil, the grains annual losses caused by insects and arthropods infestation are estimated at 2 billion dollars, calculated as function of weight, volume and quality losses.

According to [1], in 2001, the quantitative average losses of grains in Brazil, estimated by the Ministry of Agriculture, Livestock and Supply are approximately 10% of the annual production. However the losses in quality are even greater, since that deteriorated grains have smaller monetary value.

Loeck (2002) [10] and Elias et. al (2008) [8] argue that periodic sampling is one of the most effective methods to indetify insects in grains. However, to collect such samples requires high cost of labor. Also, considering a real metal silo (as illustrated in Fig. 2), the sampling is a complicated process given that to take distributed samples throughout the storage is a very difficult task. This process can be greatly simplified by the installation of endoscopic cameras in silos and then perform computer vision analysis to determinate if there are insects in the grains.

In this work we analyse the presence of insects in maize. Cornfields cover around 20 millions hectares in Brazil with a average production around of 80 millions tons/year of maize. Aiming at avoid losses during harvest due rainy periods, growers normally crop once a year. The cropped maize grains are stored for approximately a year, being highly susceptible to weight and quality losses due to insects infestation mainly. Estimates suggest that, in Brazil, the post-harvest losses in maize are of about 14% of the total weight. Apart from causing quantitative losses, insects in stored grain are also linked to aflatoxin contamination that can lead to poisoning of living beings that eat the grains.

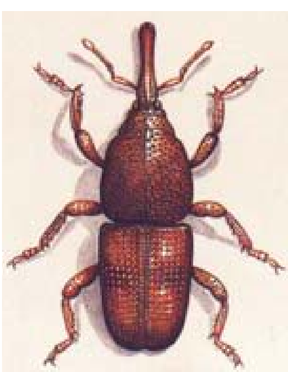
In Brazil, the maize weevil (Sitophilus zeamais) and the brown beetle (Tribolium castaneum) are main causes of maize losses. The Figure 1 illustrate these insects.

The maize insects control have been made mainly by pesticides. However, several studies have shown that population of pesticide-resistent maize insects are emerging, in this way pesticides should be used sparingly, when the insects appear. Thereby, to avoid losses in stored grain is necessary a early detection and classification of insects in grains to quickly apply the right pesticide. Thus, automated tools based on computer vision are promising to detect moving objects inside grain's storages and to classify them, following.

There are two basic approaches to detect moving objects in videos: optical flow and background subtraction (or foreground identification). Briefly, optical flow quantifies velocity vectors of the moving objects. Once computed, the measurements of moving object velocity can be used for a wide variety of tasks ranging from scene interpretation to autonomous, and active exploration by computer vision agents [2]. Background subtraction methods estimate and keep a background model, which is subtracted from the current frame. Such subtraction produces the foreground that is a delimitation of the moving objets. In this investigation we

Method ID	Method name	Reference	Settings
Basic method: mean and variance over time			
AdaptiveBackgroundLearning	Adaptive Background Learning	[14]	$T = 15$, $\alpha = 0.5$
Fuzzy based method			
FuzzyChoquetIntegral	Fuzzy Choquet Integral	[5]	$T = 0.67$, $LF = 10$, $\alpha_{learn} = 0.5$, $\alpha_{update} = 0.05$, *RGB + LBP*
Statistical method using one Gaussian			
DPWrenGABGS	Gaussian Average	[15]	$T = 12.15$, $LF = 30$, $\alpha = 0.05$
Statistical method using multiple gaussians			
MixtureOfGaussianV1BGS	Gaussian Mixture Model	[9]	$T = 10$, $\alpha = 0.01$
Type-2 Fuzzy based method			
T2FGMM_UM	Type-2 Fuzzy GMM-UM	[6], [7], [3]	$T = 1$, $k_m = 2.5$, $n = 3$, $\alpha = 0.01$
Statistical method using color and texture features			
MultiLayerBGS	Multi-Layer BGS	[16]	Original default parameters from [16]
Method based on eigenvalues and eigenvectors			
DPEigenbackgroundBGS	Eigenbackground/ SL-PCA	[12]	$T = 255$, $HS = 10$, $ED = 10$
Neural method			
LBAdaptiveSOM	Adaptive SOM	[11]	$LR= 180$, $LR_{training} = 255$, $\sigma = 100$, $\sigma_{training} = 240$, $TS = 40$

Table 1: Background subtraction algorithms used and the parameters settings of each algorithm. The parameter settings used are the same of Sobral and Vacavant investigation [14].



(a)

(b)

Fig. 1: Maize insects: (a) the maize weevil (Sitophilus zeamais); (b) brown beetle (Tribolium castaneum). Sitophilus zeamais photo is taken from http://www.cnpms.embrapa.br/publicacoes/publica/2006/circular/Circ_84.pdf and the Tribolium castaneum photo is taken from http://www.pragas.com.br/poscolheita/pragasgraos/besouros/besouros.php.

Fig. 2: Metal silo. Photo taken from www.agencia.cnptia.embrapa.br

focus on background subtraction method because different species of maize insets have particular shapes that allows to classify such species.

Several studies revels that to classify objets in video correctly, segmentation of moving objets play a fundamental role. In this research, we propose a segmentation method of moving objets and compare them with the best methods from the literature, according to the Sobral and Vacavant investigation [14]. Although several studies compare background subtraction methods, to the author's knowledge, this is the first study to compare such methods to segment moving insects in grains using endoscopic video. Experiments with real videos, obtained with an endoscopy camera, reveal that the proposed method produces more precise segmentation result than state-of-art methods.

The remainder of this article is organized as follows: section 2 describes the main concepts of background subtraction techniques and presents the proposed background subtraction method; section 3 lists the methods used in our comparative study and describes the experimental results. Finally, the section 4 summarizes the main contributions of this investigation.

2. Proposed Method

Several methods for background subtraction have been proposed to track objects of interest in a scene. Basically, all of these methods try to effectively estimate a background model from a temporal sequence of frames. The background model is first initialised and then maintained along the time. To estimate the foreground, i.e., the moving objects, the current frame is subtracted from the current background model. There is a wide variety of techniques for estimate a background model. A reader interested in the subject may like to consult review papers as [4], [13], [14].

This section describes the main steps of the proposed algorithm.

2.1 Background Bootstrapping

An important step to every background subtraction method is initialise the background model, which in most cases do not have a starting clear background sequence of frames to build it. This step is called Bootstrapping and has to be fast and accurate. Therefore, a robust approach must be created to initialise the background model as quickly as possible. Our approach partitions the image into blocks (of 16x16 pixels) and only adds this region to the background model if high portions of the pixels are not moving. To determine if the pixels are not moving we analyse two consecutive frames. If more than 90% of the pixels in the block still have the same value, they are not moving. If it happens for more than 5 times consecutively, the block is set to "ready" and no more checked. Once all blocks are classified as "ready", the initial background is determined.

2.2 Background Updating

In our scenario, the insects are in constant movement and frequently push the maise skin, which should be considered as background. Therefore, updating the background becomes an essential step. That is the motivation to implement the learning rate background updating. After the bootstrapping step the background is updated considering every frame at time t in the video. Each new input frame I_t updates the background BG_t according to Eq 1.

$$BG_t = (\alpha * I_t) + ((1 - \alpha) * BG_{t-1}) \qquad (1)$$

where α is the learning rate that determines how fast the background absorbs the moving objects, which in this case can be a high value, due to the high velocity of the insects. Our preliminary tests show that 0.01 produces good results, but could be better estimated if the velocity of the insects were measured to weigh the α value.

2.3 Foreground Extraction and Binarization

To determine the mask, or foreground, the algorithm proposed uses the background difference technique to remove the background frame by frame. The difference between the current frame and the background is determined by:

$$M_t(i,j) = \frac{(I_t(i,j) - BG_t(i,j)) * i^T}{3} \qquad (2)$$

where i^T is de identity vector, $I_t(i,j)$ and $BG_t(i,j)$ are the vector (R,G,B) of pixel (i,j). M_t is a two-dimensional array at time t that represents the gray-scale intensity level of each pixel. The Fig. 3 below shows a mask example.

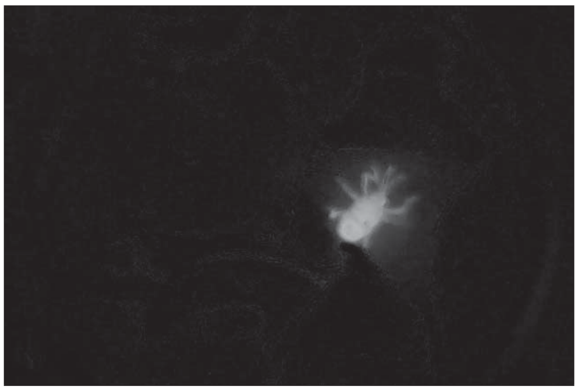
Given that the mask contains the moving object, we use the thresholding technique to determine which pixels are relevant and will be presented on the binarized image. The Fig. 4 shows the binarized mask of the example above.

3. Results

Our video data set consists on short-time videos recorded within a metal silo using an endoscopic camera with resolution of 640x426 pixels. The use of a low resolution camera is motivated by its low cost that became feasible for a real-world application in metal silos, where is required around of hundred endoscopic cameras.

To compare the proposed method we choose the best background subtraction algorithms reported in the recent review by Sobral and Vacavant [14] and implemented by the same authors in the BGS library available in https://github.com/andrewssobral/bgslibrary. The Table 1 lists the methods of BGS Library used and the settings for each of them. The settings used for each methods are the same used by Sobral and Vacavant in [14]. For more details about each method, the reader is referred to reference [14]. The Figures 5 and 6 show the results applying the proposed method and the selected state of art methods in four different frames extracted from our data set. In an visual analysis one can see that our approach delineates more precisely the insect's shape. Among the experimented methods, those who achieved more accurate results are our approach, MixtureOfGaussianV1BGS, LBAdaptiveSOM and MultiLayerBGS, respectively.

(a)



(b)

Fig. 3: (a) Original image and (b) mask

Fig. 4: Binarized mask with threshold 75

4. Conclusion

As known from many researches, object segmentation plays a crucial role in computer vision systems aimed to classify objects. In this study we present a object segmentation method based on the background subtraction technique. Our experiments using a video data set containing insects shows that the proposed method achieves more accurate segmentation results than state-of-art background subtraction methods listed in a recent research review. As object segmentation play a key role in object classification, our results indicate that the proposed method can be applied to build a insects recognition approach with more accurate results than when using others background subtraction methods. Additionally, to the best of our knowledge, this is the first study carried out to compare background subtraction methods applied to insect segmentation from endoscopic videos. As future investigation we intend to experiment the proposed methods in another object segmentation domains.

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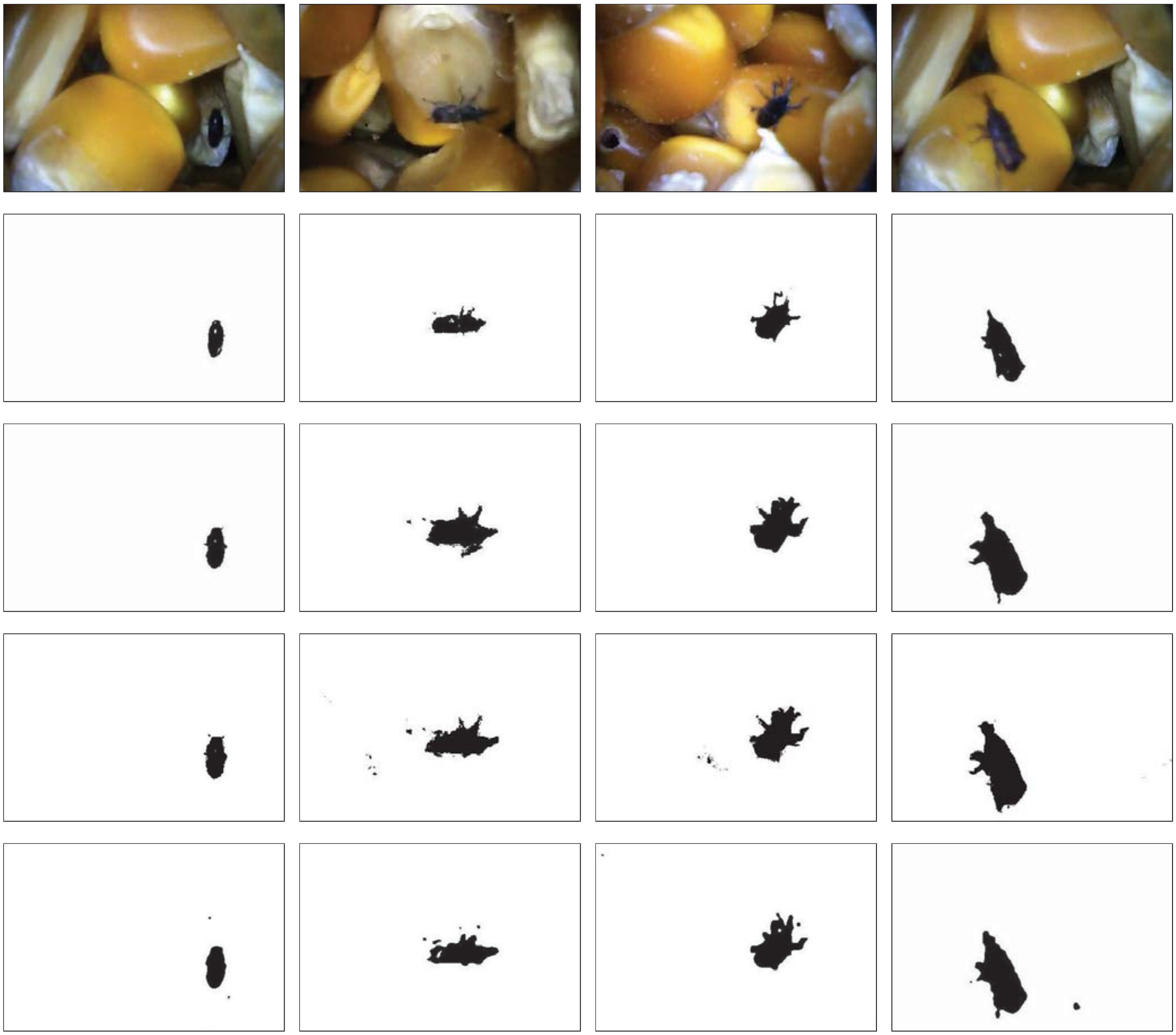

Fig. 5: Original imagens in the first row and Result obtained by the methods analysed: second row – proposed method; third row – MixtureOfGaussianV1BGS; fourth row – LBAdaptiveSOM; fifth row – MultiLayerBGS. The settings of each algorithm are given in the Table 1.

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Fig. 6: This Fig. is a continuation of Fig. 5. Original imagens in the first row and Result obtained by the methods analysed: second row – DPWrenGABGS; third row – DPEigenbackgroundBGS; fourth row – AdaptiveBackgroundLearning; fifth row – FuzzyChoquetIntegral; sixth row – T2FGMM_UM. The settings of each algorithm are given in the Table 1.