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Real Time Vision Based Obstacle Detection System for Micro Aerial Vehicles Navigation using Support Vector Machines

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Abstract—In this paper, a real-time vision based obstacle detection system for Micro Aerial Vehicles (MAVs) navigation using Support Vector Machines. In the feature extraction stage, features, namely, Haralick Features, Color Histogram Features and Hu Moments Features were extracted from the acquired image frames using raspberry pi 3 camera. Vision based obstacle detection algorithm is implemented on raspberry pi 3 single board computer. In the training phase, 180 images (90 images with obstacle and 90 images without obstacle) are used for training and 20 images (10 images with obstacle and 10 images without obstacle). Support Vector Machines (SVM) classifier is used to classify the acquired test image frame with and without obstacle. This obstacle detection information can be used to avoid collision with the static and dynamic obstacles in the forward flight path of MAV. Experimental results on the different test image frames demonstrate that the proposed vision based obstacle detection algorithm based on Haralick Features, Color Histogram Features and Hu Moments Features extracted for the test image frame and classified with Gaussian kernel SVM Classifier produces high classification accuracy of 78.33 % compared to linear, sigmoid and polynomial kernel SVM classifier.

Keywords— Object detection, Raspberry Pi, Support Vector Machine, Micro Aerial Vehicle

I. INTRODUCTION

An object identification framework discovers objects in reality from a picture, utilizing mechanized calculations. The object discovery problem can be characterized as a grouping issue including object class and non-object class pictures. Formally, given a picture containing at least one object of interest alongside the background and a lot of labels comparing to a lot of pictures known to the framework, the framework needs to allot correct labels to each picture. Object recognition can be utilized in wide range of fields such as, for example, reconnaissance and security, programmed flight control and vehicle tracking [1].

In any case, constructing an object recognition framework has been a difficult procedure, independent to the strategy utilized, because of different changes in the pictures with and without objects. Changes can't happen just while changing the objects but also when a similar object changes position or when the lighting conditions are modified and are not consistent. On account of all these, all object recognition frameworks, until present compromise between two principle requirements: performance and robustness [2]. Once the obstacles are detected using the proposed method, a suitable Pulse Width Modulated signal can be transmitted from the Arduino board (Collision Avoidance System) to the pitch channel of the flight controller board to pitch the MAV backwards to avoid collision with the static and dynamic obstacles.

In pattern recognition and image processing, feature extraction is an important method of dimensionality reduction. The important requirement of feature extraction is to obtain the most relevant information from the original data and characterize the information in a lower dimensionality space. A feature set contains selective information, which can differentiate one item from other items. The feature extraction algorithm needs to be as robust as possible for preventing the generation of different features which are similar to each other. The certain set of features must be a minor set whose values efficiently distinguish patterns of dissimilar classes, but are comparable for patterns within the same class [1, 2].

Features can be classified into two types [3]:
1. Local features, which are typically geometric (e.g. concave/convex parts, number of end-points, branches, Joints, etc).

2. Global features, which are usually topological (e.g. connectivity, projection profiles, number of holes, or statistical methods, etc).

Machine Learning is considered as a subfield of Artificial Intelligence and deals with the synthesis of techniques and methods which allow the computer to learn and think [1]. Support Vector Machine (SVM) was first demonstrated in 1992, and introduced by Boser, Guyon, and Vapnik in COLT-92. Support vector machines (SVMs) are a set of connected supervised learning methods used for classification and regression [1]. They fit into a family of generalized linear classifiers. In another terms, Support Vector Machine (SVM) is a tool for performing classification and regression that uses machine learning theory to maximize accuracy while routinely avoiding over-fitting problems [2]. The basics of Support Vector Machines (SVM) have been established by Vapnik [4] and expanded popularity due to many important features such as better empirical performance. The construction utilizes the Structural Risk Minimization (SRM) principle, which has been demonstrated to be superior, [4], to the traditional Empirical Risk Minimization (ERM) principle, used by conventional neural networks. SRM minimizes an upper bound on the expected risk, while ERM minimizes the error on the training data [5]. SVM is successful when utilized for pattern classification problems. One of the major tasks is in the selection of an appropriate kernel for the given problem [4]. There are standard adoptions such as a Gaussian or polynomial kernel that are the standard options, but if these prove unsuccessful or if the inputs are complex, more intricate kernels are required [6, 7]. Rest of the paper is organized as follows, Section I contains the introduction of vision based obstacle detection system for navigation of Micro Aerial Vehicle. Section II contain the methodology of the proposed work for obstacle detection using Raspberry Pi 3 single board computer. Section III contain the results and discussions of the proposed work and section V concludes the proposed research work.

II. METHODOLOGY

A real time object recognition scheme must have the following mechanisms to achieve the task [8-14]:

- The image database.
- Feature extraction procedures.
- A classification procedure for classifying the pictures.
- A hardware unit capable of storing and executing the above-mentioned tasks.

The block diagram of the work reported in this paper is depicted in Figure 1.

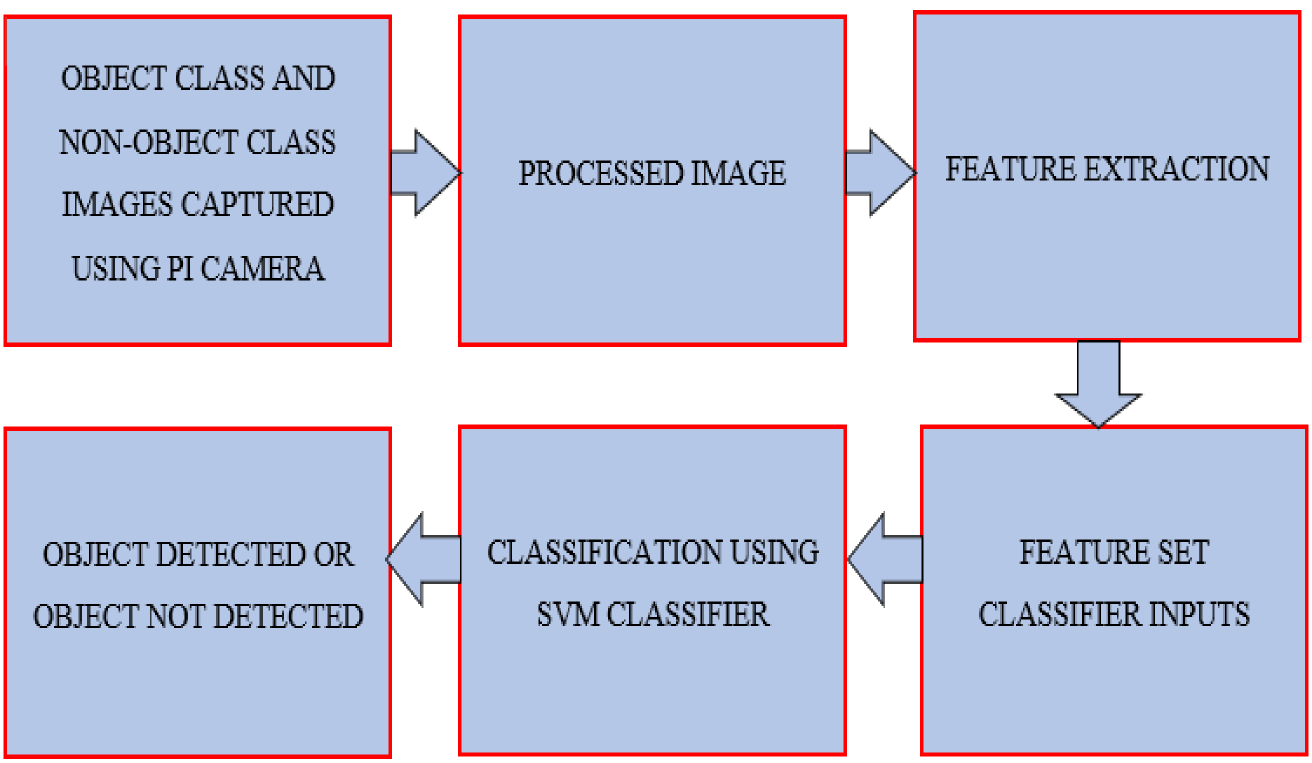


Figure 1. Block diagram of the proposed methodology for obstacle detection

A. The Raspberry Pi 3 Microcontroller

In view of the rather high-performance necessities of image processing, and the microcontrollers currently accessible, as a comparatively inexpensive and powerful embedded platform, the Raspberry Pi microcontroller is an effective platform. The original Raspberry Pi is based on the Broadcom BCM2835 System on a Chip (SoC), which includes an ARM1176JZF-S700 MHz processor, Video Core IV GPU, and originally emanates with 512 MB RAM. The system has Secure Digital (SD) or MicroSD sockets for boot media and persistent storage. The Raspberry Pi Camera Module is an authorized product from the Raspberry Pi foundation. The original 5-megapixel model was released in 2013, and an 8-megapixel Camera Module v2 was released in 2016. For both iterations, there are visible light and infrared versions.

B. Feature Extraction

In pattern recognition and image processing, feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed easily, and is also redundant, then the input data needs to be transformed into a abridged set of features. Transforming the input image into a set of numerical features is called feature extraction process [9]. If the features extracted are cautiously selected, it is likely that the feature set will have the appropriate and required information from the input image in order to accomplish the chosen task using the reduced feature set instead of the full-size image input. Features contain information related to gray levels, texture, shape or contrast. To classify an object or item in an image, it is required to first extract few features out of the image. In this work, Grey Level Co-occurance Matrix features, Color Histogram Features and Hu Moments, were the extracted features for the classification of object class and non-object class images.

C. Support Vector Machines

In a given set of points which belong to one of the two classes, SVM provides an optimal way to separate the two classes by a hyperplane. This is performed by [14]:

- maximizing the distance of either class to the separating hyperplane
- minimizing the risk of misclassifying the training samples and the unobserved test samples.

Depending on the way, the given points are divided into the two available classes, the SVMs can be classified into:

- Linear SVM
- Non-Linear SVM

SVM provides a mapping of the data points from the input space R^d into higher dimension R^n (n > d) space using a function $\Phi: R^d \rightarrow R^n$. Then the training algorithm will depend only on dot products of the form $\Phi(x_i)\cdot\Phi(x_j)$. Constructing (via Φ) a separating hyperplane with maximum margin in the higher-dimensional space produces a nonlinear decision boundary in the input space. Because of the computational complexity involved, the kernel functions are utilized. A kernel function K such that $K(x_i,x_j)=\Phi(x_i)\cdot\Phi(x_j)$ is used in the training algorithm.

The classes for Kernel Functions used in SVM are:

Polynomial Kernel:

$$K(x,x')=(x\cdot x'+c)^q$$

RBF (Radial Basis Function) Kernel:

$$K(x,x')=e^{-\frac{\|x-x'\|^2}{2\sigma^2}}$$

Sigmoid Kernel:

$$K(x,x')=\tanh(\alpha x\cdot x'+b)$$

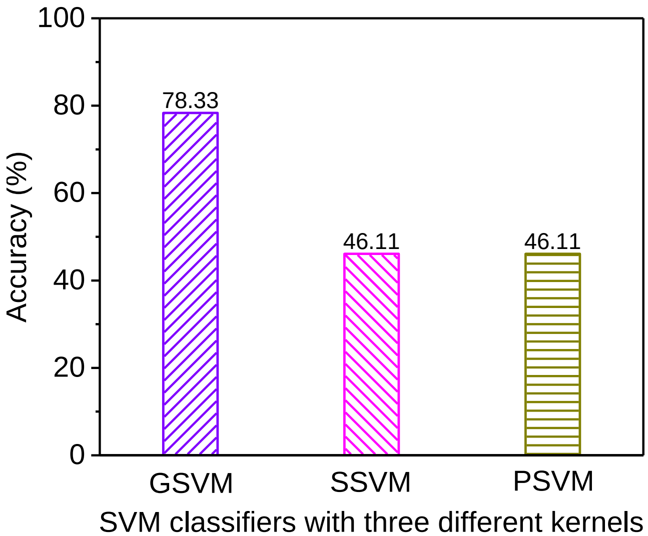
The kernel functions require calculations in $x(\in R^d)$, therefore they are not difficult to compute. It remains to determine which kernel function K can be associated with a given function Φ [15].

III. RESULTS AND DISCUSSION

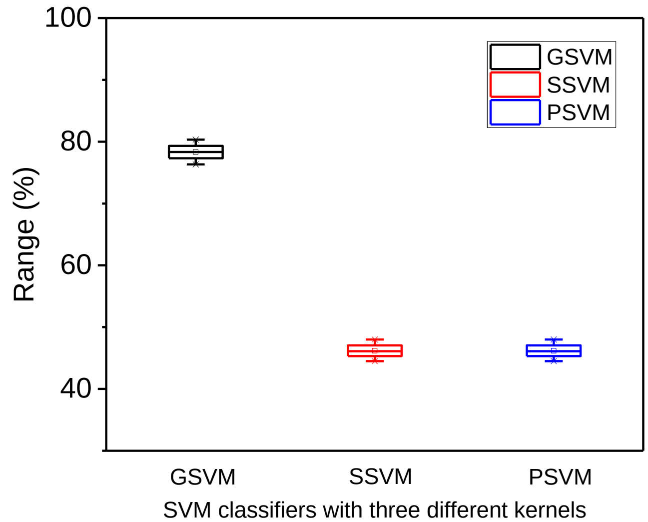
In this work, the SVM classifier with three different kernels such as Gaussian, sigmoid and polynomial (with order of 8) kernels were adopted to classify the images with and without obstacles. Further, the total of 180 images was taken with the help of Raspberry PI camera and was used to train the SVM classifier with different kernels. Also, the Raspberry PI camera captures total of 20 images during testing and it is stored inside the Raspberry PI microcontroller. The SVM classifier code was developed using python software and the Raspberry PI microcontroller executes the code and produces the classification output. It is observed that the total of 180 images (with and without obstacle) is used to train the classifier and once the trained classifier model is developed, the total of 20 images (with and without obstacle) is used for testing purpose. Further, it is seen that the accuracy and the Standard Deviation (SD) of GSVM classifier is 78.33% and 2.056 respectively. It is observed that the accuracy of SSVM classifier is 46.11% and the SD is 0.056. Also, the accuracy and SD of PSVM classifier is same as the SSVM classifier.

Figure 2 (a). shows the accuracy of three different classifiers such as GSVM, SSVM and PSVM respectively. It is seen that the accuracy of GSVM classifier is high when compared to the other two SVM classifiers. Also, it is observed that the accuracy of SSVM and PSVM classifiers are same.

Figure 2 (b). shows the accuracy range comparison of three different SVM classifiers such as GSVM, SSVM and PSVM using box plot representation. By comparing the performance of three different SVM classifiers, the Gaussian SVM is good at classifying the images with and without obstacle than the other two SVM classifiers namely Sigmoid SVM classifier and Polynomial SVM classifier. Table 1 compares the accuracy of linear and nonlinear SVM's.



(a)



(b)

Figure 2. Accuracy of three different SVM classifiers (a). Accuracy of SVM classifiers with three different kernels (b). Comparison of three different SVM classifiers

Table 1. Performance parameter of different classifiers

S. No.	Classifier Types	Accuracy
1.	Linear SVM Classifier	22.22
2.	Gaussian SVM Classifier	78.33
3.	Sigmoid SVM Classifier	46.11
4.	Polynomial SVM Classifier (order = 8)	46.11

IV. CONCLUSION

This paper has described real-time vision based obstacle detection system for Micro Aerial Vehicles (MAVs) navigation using Support Vector Machines. Gaussian kernel SVM classifier is suitable for the categorization of images with and without obstacle. From the experimental result, it is inferred that the proposed vision based obstacle detection algorithm based on Haralick Features, Color Histogram Features and Hu Moments Features extracted for the test image frame and classified with Gaussian kernel SVM Classifier produces high classification accuracy of 78.33 % compared to linear, sigmoid and polynomial kernel SVM classifier. Obstacle detection result of vision based obstacle detection algorithm can be used for avoiding collision with the static and dynamic obstacles in the forward flight path of MAV. The proposed algorithm can be used in the collision avoidance system to avoid collision with the static and dynamic obstacles in the forward flight path of MAV. In the future work, global image features and other kernels for SVM will be investigated for improving the classification accuracy in the detection of obstacle.

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