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TWO-STAGE SEGMENTATION OF AERIAL IMAGES FOR SEARCH AND RESCUE

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Abstract. This paper presents a novel two-stage image segmentation approach for detection of artificial materials and objects in non-urban terrain. It is based on the assumption that an object and a natural background have different color/saturation. High resolution image of the unknown terrain taken with digital camera from a distance of about 100 m is divided into smaller sub-images for further processing. Each sub-image is clustered using mean shift algorithm, and information about obtained cluster centers is transferred to the next stage. Second stage uses information about cluster centers from all sub-images and applies the same clustering method to this data set. Finally, a decision-making module evaluates all clusters and eventually proposes image segments that have high possibility of presenting the artificial material or the object in the input image. The proposed method has been tested on 22 aerial images typical for search and rescue. Observed results are validated through recall and precision and it has been shown that the proposed method can be successfully used for real search and rescue operations.

Keywords: image segmentation, mean shift, object detection, aerial images, search and rescue.

1. Introduction

Surveillance of various terrains in order to find some object of interest is a task that can be associated with various civil and military activities. Typical examples include man-made object detection, natural object detection and tracing moving objects.

Although some other sensors (like Synthetic Aperture Radar and Infrared camera) are also used, for such kind of tasks aerial photos are most commonly used. Aerial or long distance photos (including satellite images) are used for road detection [1], building detection [2],[3], airplane detection [4] and other man made objects detection. It is also used for soil-type detection, vegetation-type detection [5] and other natural objects/phenomena detection. Also, an important issue that is dealt with is tracking the moving object, because many of the applications are oriented towards traffic surveillance and object tracking (humans, animals, etc).

Our paper deals with human detection for the Search and Rescue (SAR) application, i.e. finding lost, hurt or persons that are in some kind of danger. Note that, in our case, motion information obtained from the acquired sequences of images (or video) is non-relevant because the individuals searched for are mainly non-moving. It means that the focus of our research will be image processing of static images.

In SAR missions, large areas of generally unfamiliar terrain must be thoroughly inspected. As a consequence, such missions can last for several days and can demand large and diverse task forces and various technical support. Therefore, significant financial and human resources are needed. Among those resources is aerial searching.

As an additional support and, sometimes, the only possible option, is introduction of autonomous inspection of the area of interest that includes some kind of image processing and/or artificial intelligence. Surprisingly, there are very limited number of articles regarding automatic human detection from aerial images. Moreover, except searching for crashed airplanes, there are a very limited number of articles dealing with search and rescue using aerial images at all.

Articles presenting algorithms and methods for search and rescue missions are mainly focused on on-ground rescue that includes processing of images taken from short range and with sensor fusion. Specificity of these kinds of applications is detection of shapes corresponding to human parts [6, 7]. However, object shapes are not likely to be helpful in detection of humans from the images taken from long distances (due to occlusions, resolution limitations, …) such as aerial photos taken from a helicopter or airplane.

There are also papers that deal with object detection in nature background based on image discrimination [8]. Basically, in these approaches, the difference between a pair of images is calculated in order to find an object. Presumption is that there are prerecorded images of terrain (i.e. image without object) which is realistic only for surveillance applications and not for SAR missions.

In this paper we are proposing a new method for human detection, or more general, for the detection of non-natural materials. Our method is based on image segmentation and color difference between natural and non-natural materials. Moreover, we have developed a new two-stage approach for image segmentation that significantly speeds-up segmentation with negligible performance reduction.

There are only several similar approaches reported in literature. Sumimoto et al. [9] depicted an image processing system for the detection of the rescue target in marine casualty. They have used a different approach based on segmentation and color difference between target and environment. But the environment they used was the Ocean, which is an environment that is much simpler than the general non-urban environment that we are dealing with. They perform their tests on orange buoy with a 3 m diameter.

Wesall et al [10] have also developed a system for aerial search in maritime environment based on completely different presumptions. They have been searching for a human (head with shoulders) which is a very small object in a relatively homogenous environment. So their approach was an attempt to distinguish a small target from noise. They used temporal information since the object in the maritime environment is actually moving.

Recently, Eismann et al [18] proposed a combined visible/near-infrared hyperspectral imaging system that provides information related to surface material characteristics and is intended to use for search and rescue.

The rest of the paper is organized as follows. Section 2 presents motivation and previous work. Section 3 explains the algorithm and method we have used, as well as the proposed two-stage segmentation approach. Results are presented in section 4. Conclusions are made in section 5 and acknowledgements are given in section 6.

2. Motivation and previous work

Search and rescue (SAR) missions for lost persons are an everyday task in most countries. SAR missions are generally connected with non-urban (or at least sub-urban) terrain: mountains, forests, sea, deserts, etc. Usually, relatively large terrain should be searched. There are many resources that may be used for search missions: human trackers, searching and tracking dogs, aerial searching, and infrared cameras.

Our focus is aerial searching. Currently, aerial searching is conducted by naked eye and, when closer inspection of a particular area is needed, binoculars are used as an aid. Occasionally, generally on large missions with a lot of public attention, a series of photos of the searching area are taken from air to be visually inspected later.

Both approaches have some disadvantages. According to [11] Probability of Detection (POD) for aerial search for lost persons with coverage 1 is 64% and with coverage 2 is 86%. Although search theory is beyond the scope of this paper, we can say that coverage 1 means that each part of the searching terrain will be at least once visually inspected. For example, to achieve coverage 1 in mountainous terrain, flying altitude should be about 100 meters with flying distance of 200 meters, and to achieve coverage 2 flying distance should be a 100 meters. In reality such conditions can be achieved only above sea or desert.

On inland terrain, especially mountainous, it is almost impossible to maintain constant flying height and speed, as well as flying distance between consecutive searches. It means that the probability of detection is almost always significantly lower than mentioned above. Of course, if enough resources are applied, probability of detection can approach a 100%. Unfortunately, this is not always an option, because resources are almost always limited. Moreover, usually there are weather constraints which make aircraft usage possible only for a relatively short period of time. Otherwise, it becomes dangerous for the crew, the searchers and the aircraft.

This means that direct visual inspection from the air does not guarantee that a missing person will be found. Moreover, even photo-taking and later inspection does not guarantee finding the person. Namely, at least several hundreds, sometimes thousands of photos are taken in each mission. Visual inspection of so many pictures is hard and a time-demanding task, and still there is a possibility that lost persons will be omitted. Of course, this is not a real time approach, and finding a person several hours later may make the difference between life and death.

“Looking and not seeing” is a well-known problem in human search. That problem will be, at least partially, avoided in an image processing system.

It means that current and future observation systems provide a large amount of data, which can hardly be completely processed manually: therefore, automatic systems are required for image interpretation. Automatic human detection from long-range images is a challenging problem since both precision and recall must be optimized. Humans must not be missed and false alarms must be reduced to a minimum.

On the other hand, robustness and computational efficiency are critical issues in operational contexts. An algorithm must be particularly robust to scenes and conditions changes. Also, no parameterization should occur, in order to be used by non-experts. Usually implementation should run in real-time and on constrained systems.

Satisfactory solution will be a real time image processing approach that is comparable to human searchers which means that it should achieve at least 64% Probability of detection - POD (assuming that the photo is taken at least once for each part of searched area). Of course, taking more photos from different angles and positions should mean higher POD, just like in human search.

In our previous research, various image segmentation algorithms were investigated [13] and the mean shift algorithm has been chosen as the algorithm that demonstrated the best results regarding quality of segmentation and stability. Also, there is no need to define the number of segments. Basically, mean shift algorithm has nonparametric nature with minimal user input.

However, major drawback of mean shift algorithm is a high computation requirement which, of course, means high processing time. The quadratic computational complexity of the algorithm is a significant problem for practical applications of this algorithm.

In our case, logical approach to handle computation problem will be splitting of the whole image into several sub-images. It can significantly reduce computation time (depending on the number of sub-images) but unfortunately it also significantly increases the number of false alarms.

False alarms will occur if the color of the natural object (an object that we are not looking for - for example plant) is different from the rest of the (sub)-image. Logically, the bigger the (sub)-image is the less chance that this object will be the only one with that specific color (actually we are looking for up to three objects with the same specific color) and consequently chances are less to have a false alarm. In this paper we are proposing a two-stage segmentation approach that reduces processing time while keeping the same recognition rate (recall) and also keeping precision at the acceptable level.

Choice of the color space used in a particular computer vision application is not a trivial task because different color spaces have different advantages and disadvantages [15]. It can be stated that the traditional RGB color space is not convenient for these kinds of applications due to the high correlation between color components. For computer vision applications, HSI (HSV) and YCbCr color spaces are, generally, the better choice. We have made a comparison of segmentation results obtained for HSI and YCbCr color space and the results showed that processing in YCbCr color space produces slightly better results regarding precision [12].

We have also investigated the relationship between hue/saturation and distance from the object to the camera for natural and artificial materials [14] (distances up to 200 meters). We have concluded that hue and saturation are significantly different for natural (i.e. forest, grass, rocks, etc.) and artificial materials.

Preliminary results of the method presented in this paper are given in [19] but based on a small set of test images. Also, here we are providing detailed procedure description as well as the performance analysis that includes precision and recall.

3. Proposed method

3.1. Procedure overview

The whole procedure can be presented as a three phase process (Figure 1): preprocessing, segmentation and decision.

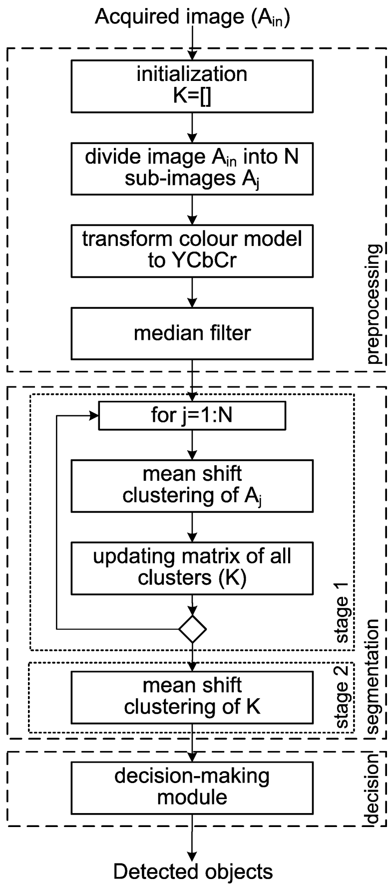

Figure 1. Procedure overview

First phase comprise initialization, division of original image into sub-images, transformation of color model to YCbCr and median filtering of image.

Second phase is segmentation realized through two stages. First stage is data clustering of each sub-image. It should be pointed out that the output of this stage is a matrix (K) containing information of all the clusters in the original image. Complete cluster matrix K is obtained by merging resulting cluster matrices of sub-image clustering.

Second stage of the segmentation phase comprises clustering of cluster matrix K. Instead of clustering of sub-image pixel values that is used in the first stage, clustering in this stage uses cluster centers (mean Cb and mean Cr for each cluster) as input points. We introduced this two stage approach in order to speed up segmentation keeping almost the same performance.

Of course, this approach can also be used for other problems.

This approach assures that the number of points for data clustering stays reasonably low in both stages. The number of pixels in sub-images (stage 1) is, of course, N times smaller than the number of pixels in the original image and the number of cluster centers in the second stage is even smaller than the first one.

Third phase is a decision-making module in which the clusters are processed in order to decide if some of them contains human (non-natural material).

3.2. Image preprocessing

Preprocessing module (first phase) consists of initialization, division of original image into sub-images, transformation of color model to YCbCr and median filtering.

Median filtering is done on blue-difference chroma component (Cb) and red-difference chroma component (Cr). Filtered Cb and Cr components are used as the input to the second phase (segmentation).

3.3. Mean shift algorithm

The mean shift algorithm [16] is a nonparametric clustering technique which does not require prior knowledge of the number of clusters, and does not constrain the shape of the clusters. Given *n* data points x_i, i = 1, ..., n on a d-dimensional space R^d, the multivariate kernel density estimate obtained with kernel *K(x)* and window radius *h* (bandwidth) is

$$f(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right). \tag{1}$$

For radially symmetric kernels, it suffices to define the profile of the kernel *k(x)* satisfying

$$K(x) = c_{k,d} k\left(\|x\|^2\right), \tag{2}$$

where $c_{k,d}$ is a normalization constant which assures *K(x)* integrates to 1. The modes of the density function are located at the zeros of the gradient function $\nabla f(x) = 0$. The gradient of the density estimator (1) is

$$\begin{aligned}\nabla f(x) &= \frac{2c_{k,d}}{nh^{d+2}} \sum_{i=1}^{n} (x_i - x) g\left(\left\|\frac{x - x_i}{h}\right\|^2\right) \\ &= \frac{2c_{k,d}}{nh^{d+2}} \left[\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)\right] \left[\frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)} - x\right],\end{aligned} \tag{3}$$

where $g(s) = -k'(s)$. The first term is proportional to the density estimate at x computed with kernel $G(x) = c_{g,d} \cdot g\left(\|x\|^2\right)$ and the second term

$$m_h(x) = \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)} - x \tag{4}$$

is the mean shift. The mean shift vector always points toward the direction of the maximum increase in the density. The mean shift procedure, obtained by successive computation of the mean shift vector $m_h\left(x^t\right)$ and translation of the window $x^{t+1} = x^t + m_h\left(x^t\right)$ is guaranteed to converge to a point where the gradient of density function is zero.

The mean shift clustering algorithm is a practical application of the mode finding procedure:

- starting on the data points, run mean shift procedure to find the stationary points of the density function,
- prune these points by retaining only the local maximum.

The set of all locations that converge to the same mode defines the basin of attraction of that mode. The points which are in the same basin of attraction are associated with the same cluster.

3.4. Decision-making module

Decision making module has several steps. First, large clusters are erased (larger than defined threshold value). Threshold value depends on the estimated distance from the camera to the observed surface. Presupposition is that if the candidate region has more than estimated number of pixels, it means that the actual person is positioned too close to the camera and the search is trivial. This presumption efficiently eliminates the big areas from the image.

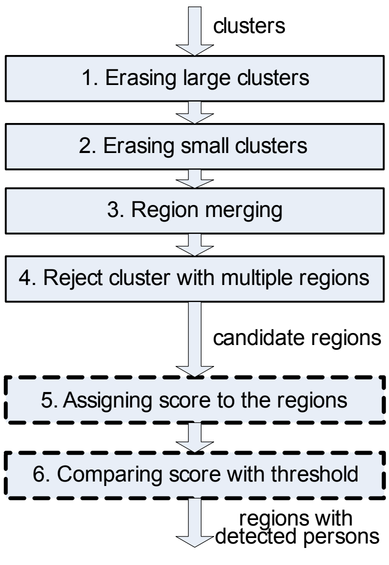

Figure 2. Decision-making module

Second step of the decision-making module erases areas inside the cluster containing too few pixels (less than the estimated threshold). In that way the noise presented by some scattered pixels left after median filtering is being eliminated. After this step, the similar nearby segments are merged.

Next step excludes those candidate segments that belong to the cluster with more than three spatially separated areas. The assumption is that there won't be more than three suspicious objects with the same color.

All the remaining regions that were not eliminated by the previous four phases are forwarded to the next two phases that are optional. The fifth phase assigns scores to the remaining region in the image according to the available data and situation knowledge. Possible information for the region scoring can be colors of the missing persons clothing, usual terrain colors, etc. It reduces the number of wrongly detected regions. To be as general as possible, presented results in Section 4 doesn't use any additional knowledge such as cloth colors. It means that candidate regions and regions with detected persons (Figure 2) are identical.

4. Results

Programming was done using the Matlab 2008a software package with Image Processing Toolbox. Computer on which the processing was done is Pentium Dual Core on 1.86 GHz and 2 Gb of RAM. Installed graphic card was GeForce 8800GT 512 DDR3.

The majority of test images were taken by the digital camera allocated in MI-8 MTV helicopter that was flying at the flight speed of around 100 km/h at different heights between 50 and 150 meters. Our image test database includes 22 images with different resolutions, but mostly 2560x1920 pixels. To be as general as possible, we use images with different type of terrain: forest, sea, coast, snow, rock, etc. All images can be seen on IPSAR project web site [17].

In order to simulate real operational situation we set parameters for all images to the same value. In that way, our system is completely non-parametric for users. All images, regardless of the size, are divided into 64 sub-images, all areas containing less than four pixels are erased, and all areas containing more than 100 pixels are excluded. Those segments that belong to the cluster with more than three spatially separated areas are also excluded.

All images were converted to standard 8-bit digitized versions of YCbCr with Cb and Cr scaled to a range of 16 to 240. Window radius (bandwidth) for mean shift algorithm was set to 4.5.

As a quality measure we have used Recall (R) and Precision (P) which is a highly useful way to measure and compare the effectiveness of an algorithm:

$$R = \frac{Correct}{Correct + Missed} \times 100 , \tag{5}$$

$$P = \frac{Correct}{Correct + FalsePositive} \times 100 . \tag{6}$$

In Table 1, recall and precision for two different approaches are given. First approach (method A) segments the original image as a whole (without subdivision). Second approach (method B) corresponds to the approach described in the previous section, i.e. it uses segmentation of sub-images (stage 1) together with segmentation of stage 2. Both approaches are using the same decision-making module as the final filtering step of possible objects.

There are altogether 29 objects in the 22 images including 5 images without any object. Note that out of 29 objects there are actually 20 humans and 9 other objects.

Usually, in the SAR missions, the searching targets are humans, but sometimes looking for some other objects is useful as well (for example car, backpack, jacket, etc). In Table 1, results for all 29 objects are presented. Considering only humans, our algorithm managed to find 16 humans for method A and 18 for method B (out of 20).

A typical original image with an object (in this case it is a person in the shadow of the tree) is shown in Figure 3. The resulting image, i.e. image with marked detected object(s) is shown in Figure 4. The enlarged part of the original image that contains the object is shown in Figure 5. Note that one logical object can actually be composed of several smaller objects (segments) with different colors that we call sub-objects. Results after applying our method show (Figure 4 and Figure 6) that actually three sub-objects were found: shirt+backpack (on men), jacket (on the right upper side from man) and shoes. These three sub-objects belong to the two clusters. Shirt+backpack and jacket belong to the same cluster although they are on two spatially separated areas. Shoes belong to the other cluster. Segmented image can be seen in Figure 7 and Figure 8. For this particular example, altogether 16 clusters were found. Visible square structure in Figure 7 and Figure 8. is due to image division into 64 sub-images and the proposed two-stage segmentation.

At the end of segmentation process there is a relatively low number of clusters on each image, on average 18. Note that, due to the nature of mean-shift algorithm, the number and composition of the clusters may be different on each execution on the same image. However, these differences occur very rarely and may be neglected especially considering particular application.

Majority of the clusters (i.e. sub-objects) that were identified as objects have less than 10 pixels. It means that it is and it will be very hard, if not impossible, to make such a system that will be able to recognize the nature of particular objects (i.e. to recognize an object as a jacket or as shoes, etc.) from such a small number of pixels. Because of that we are proposing this system that can recognize any object different from the background.

Table 1. Comparison of recall and precision for a set of input images. A – no subdivision; B – subdivision with additional segmentation

	number of objects	correct	false	miss	recall	precision
method A	29	25	4	4	86	86
method B	29	25	19	4	86	57

Also, in order to evaluate the proposed procedure, we have compared processing speed for two different approaches. The results are shown in Table 2.

Table 2. Comparison of average processing time for a set of input images. A – no subdivision; B – subdivision with additional segmentation

	average processing time (sec)
method A	574
method B	270

Figure 3. Example image (original, 2560×1920 pixels). Object-human is in the shadow of the tree

Figure 4. Example image with marked detected object(s) (the same result has been obtained for both methods)

As can be seen from Table 1, recall is 86% for both methods. Although there are no other results that our methods can be compared with, we can conclude that the proposed method is extremely efficient especially if compared to human observers (see Section 2). Also, precision is very good for Method A and acceptable for Method B. In any case, precision is good enough for real application.

On the other hand, average processing time is still a problem for real-time applications. Using two-stage segmentation, we managed to reduce processing time by more then twice but this is still not enough. In order to have real time applications, processing time should be at most tenths of seconds and we have hundreds of seconds (to be more precise, 270 seconds). Of course, the proposed method can be very efficiently used for non real-time applications or almost real-time applications, i.e. some images can be processed in real time, other images later.

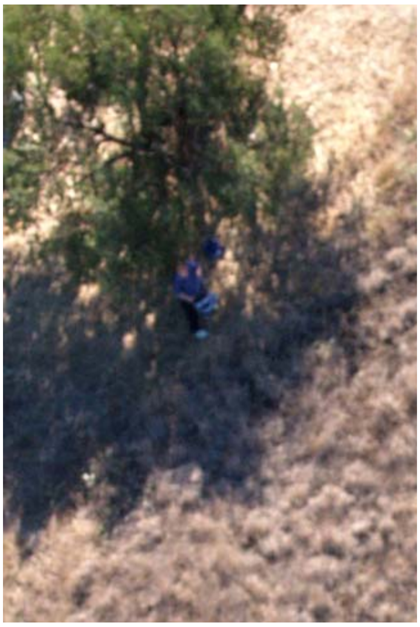

Figure 5. Enlarged part of the original image that contains an object (320×480 pixels)

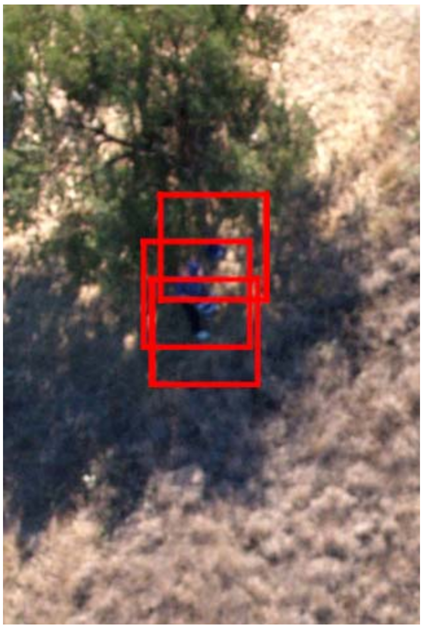

Figure 6. Enlarged part of the original image with detected object(s) (320×480 pixels)

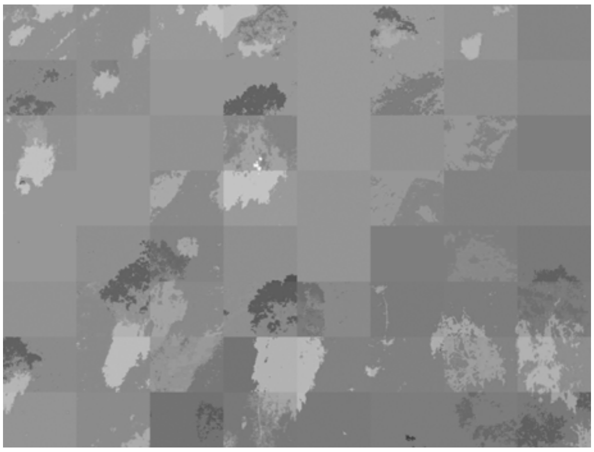

Figure 7. Typical output after segmentation.
16 clusters are found in the input image (Figure 1) after two-stage segmentation

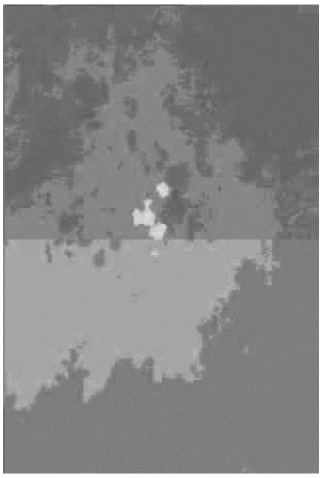

Figure 8. Enlarged part of the segmented image with detected object(s) (320×480 pixels)

The proposed procedure can easily be implemented for parallel processing on several CPU-s or exploit the capacities of modern graphical processor units (GPU-s) that have parallel "many-core" architecture. It means that real time requirement should be possible to reach using parallel processing or GPU. This, together with improvement on recall and especially precision, will be the focus of our future research.

5. Conclusion

In this paper we have presented a new two-stage segmentation approach for detection of artificial materials and objects in non-urban terrain in order to be used for search and rescue missions. High resolution image of the unknown terrain taken with the digital camera from a relatively large distance (about 100 m) is divided into smaller sub-images for further processing.

First stage of the segmentation procedure includes sub-image preprocessing and transformation of image in YCbCr color model. Cb and Cr components are used for the segmentation. Image data for each sub-image are clustered and information about obtained cluster centers is transferred to the next stage.

Second segmentation stage uses information about cluster centers from all sub-images and applies the same clustering method to this data set. Finally, decision-making module evaluates all clusters and eventually proposes segments that have high possibility of presenting artificial material or object in the input image.

We have tested the proposed method on 22 aerial images of different terrain achieving high recall (86%) while keeping the number of false alarms (precision) on acceptable level (86% and 57%).

The proposed two-stage approach is suitable for the parallel processing on modern graphical processing units. Our next step will be code translation so it could be executed on graphical processor units (GPU). Speeding of the overall processing time for at least one order of magnitude is expected so our long term objective to develop a complete, real - time system for detection of humans and other targets seams to be achievable.

Even at the present processing speed, worth of the application is very high. The system is low-cost and it allows the rescuers to obtain processed images of the very large area partly on real time, partly after the flight of helicopter within a few hours. Having the corresponding global satellite position of each image helps them in precisely locating the missing person and acting in time.

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