A NEW APPROCH TO DETECT UNDERVEHICLUAR THREATS

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Abstract

Security in today's world cannot be neglected. Terrorism has been increasing in the last few years. Terrorism today is not only restricted to the Mass Places. People have found ways of inserting objects under the cars chassis, liquid bombs in bottles, mobile bombs etc. Our idea focuses on suspicious items such as drugs, bombs, sharp dangerous objects, weapons, etc. being inserted under the chassis of the car. These objects are inserted in the car in such a way that they are not easily traceable. We propose a system which would scan the under part of the chassis of the car and given a high resolution image of the under vehicular part. Then this image is projected on screen and compared with the existing images of various cars in the database. After this any item which has been inserted or fixed in the car would be detected by our system. That particular item is then marked as a suspicious item, that particular part is then segmented out and can be viewed separately and the car is sent for further inspection.

I INTRODUCTION

There has been significant progress in finding out and detecting explosives [1]. But the Current Systems employed for traffic vehicles is to simply forge for the area under the chassis is restricted to under vehicle convex inspection mirrors [2]. These mirrors show a zoomed view of the under vehicular part. However this approach is not accurate enough as it is highly prone to human error and not being able to view the complete under part of the car. In today's world where security cannot be neglected we can not have our security system to be compromised. This calls for a system which is highly efficient and resistant to any errors in different form.

II Related Work

A lot of prior work has been done in the field of Image Stitching. Li and Wang have done automatic image stitching using SIFT [4]. Efficient and fast image registration and stitching has been done by Senarathne [5]. Juan and Guan have used SURF for stitching images in panorama mode. Researchers have achieved stitching high resolution images in the medical domain as well [6]. Zhen Hua [7] proposed a SIFT based image stitching, but it is computationally expensive for our application.

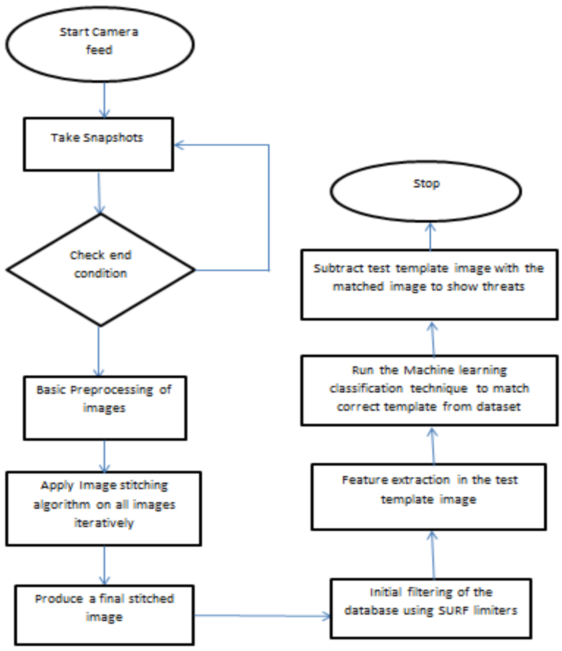
Some research has been done for matching images from huge databases. Exact matching has been done by Bosch,Ballegooij,Vries, Kersten in [8]. Punith and Guru present an effective matching technique for symbolic matching [9]. A fast and exhaustive image matching way for large database is presented in [10].

III THEORETICAL BACKGROUND

SURF algorithm is based on the finding features which are both scale as well as rotation invariant. It has been inspired from the SIFT algorithm [3]. Here we use SURF algorithm as it is fast and efficient for finding our interest points in our images. SURF points are points of interest in the image sing which we find out if 2 images are similar or not.

Correlation has also been used in the paper to find out correlation between 2 images. Pearson Correlation has been used. This is used to find the correlation between 2 images. Based on the value of correlation, we gauge the similarity of two images here.

IV BLOCK DIAGRAM



V Implementation

IMAGE REGISTRATION:
A live video feed is created. The incoming video is polled to take snap shot at regular intervals of time so long as to cover the entire image that is being scanned. Once the scan is complete and the vehicle template has crossed the camera, the capture mode is stopped. We use the fact that the camera will capture bright pixels if no vehicle is above it, i.e. we set an intelligent threshold to detect the start and end point of scan. Now we proceed through the image registration and analysis. Image registration has been there in the books and many registration techniques have been proposed till now.

We exploit the fact that the scanner would be placed on the ground and that the distance of the camera from the target object, i.e. the vehicle chassis will not change. Hence there is no need to consider the variation of depth in any two consecutive images. Also in our setup of the assembly we demonstrate that the vehicle will always pass over the scanner in a linear fashion, so we do not account for the fact that two images are drastically out of the line. We use a technique that is less computationally extensive as the image stitching/registration step might be invoked many times during the post scan process as this step will depend on the rate at which the camera is capturing snapshots from the live video feed.

We use the correlation technique for identifying the common parts in the consecutive images. We run our algorithm only over the region of interest. Region of interest is defined by taking the last 50 column pixels of the first incoming image and the first 50 columns of the second incoming image. A correspondence map is drawn between such pixels in both images. We propose two different dialects of this algorithm. The correlation function is run through both the images simultaneously and is run column wise. The correlation value of each corresponding pixel in both images is stored until the end of a vertical column is reached. Once we are able to figure out a line along the vertical elements of the matrix which has the highest coefficient, we simple take this line to be the starting point for the next image and paste the second image starting from thereon.

An improvement of this technique is that after mapping the pixels in the region of interest of both images, we find the points with a correlation value of more than a threshold, here 0.912. We define these pixels to be potential boundary pixels. We check for the 8-neighbourhood associativity of each of these potential pixels and start to connect/ store the pixels that fall in each-others 8-neighbourhood region. When we do this we find that the region of interest now consists of irregular lines that may be broken at intervals. We chose the curvy line of maximum length, i.e. the line that has maximum pixel connectivity. This curve is chosen to be the final curve along which the stitch will happen. As we already have the correspondence map for the region of interest of the two images, the second image is pasted along this curve. This stich is more accurate than the traditional max correlation based method.

IMAGE MATCHING:
Once we have the stitched image we proceed to the matching step. To match two images, we go for a two-fold matching process. First we compute the SURF points in the two images. SURF points are scale invariant points in images that remain unaffected even if there is change in the orientation of the capturing device and is also plane & size invariant. So we put a threshold on the number of SURF matches between the template image and the images present in the data base. We have already computed SURF locations of the images present in the database so we only need to run SURF algorithm once to get the scale invariant points of the template test image.

After this we define another threshold on the distance between the corresponding SURF points in the test image and the database images. A threshold is set to eliminate and reduce the database required to scan through. This step precisely identifies the chassis of similar looking vehicles. This proposed idea of thresholding the number of SURF points reduces the dataset to be scanned nearly by 98%, i.e. if we have a database of a 1000 different cars, then on applying the method suggested reduces this number to about 15-20 images.

Now we apply the matching techniques based on Machine learning on this reduced set of images. We identify features in the template image as circles (big and small separately), rectangles, squares and lines. Another important feature is the mean value of the 5x5 neighborhood of each SURF point. These features are then feed into the standard SVM technique to give out the closest match. This identifies the vehicle accurately from the database

THREAT DETECTION:
Once the test template is accurately matched with an image in the database, we simply subtract the two images to point out any perceivable threats and show them on the screen in our GUI. If the Threat is detected the GUI has a zoom feature to zoom into the region depicting threat for a closer scrutiny.

VI Results

A database of 40 different chassis was taken and a Graphical User Interface was created as shown in the figure. The GUI has different windows that displays the stitching sequence and the stitched image.

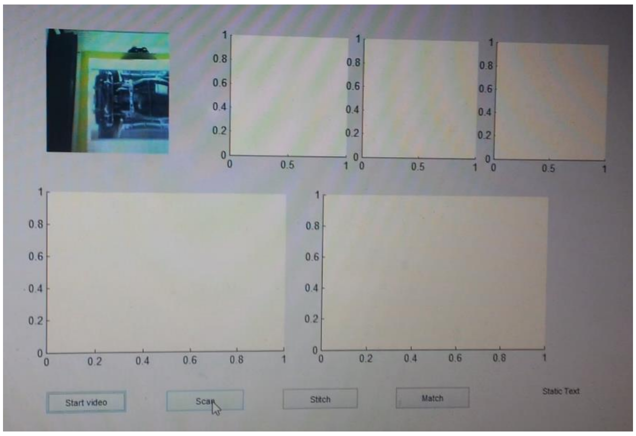


Figure 1 GUI interface in matlab which plots percentage map.

The stitched image and the corresponding matched image from database is found as shown in figure 1.

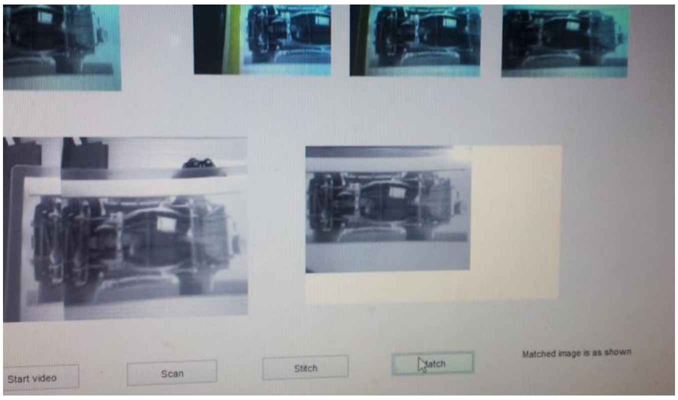


Figure 2 Shows the stitched image and can be seen is not perfect

It can be seen that at times even when the stitch is not perfect (in case of a line stich algorithm discussed earlier), we still manage to get the correct match with the database. This is due to the robustness in our approach to break the problem into smaller step checks at multiple levels. We checked for the robustness of our technique by including some other form of images altogether with same histogram as that of a typical chassis but they are different category of images. The result is still the same and it matches the correct image in the database.

VII Conclusion

We have presented a realistic implementation of an application of detecting threats from the under belly of cars using the concepts of image processing and machine learning. Future work would be to make a setup for the scanner and test out the whole setup in reality. We presented our idea and proved it by creating and simulating the prototype using MATLAB. The proposed installations could be portable and permanent ones as shown in figure 3.

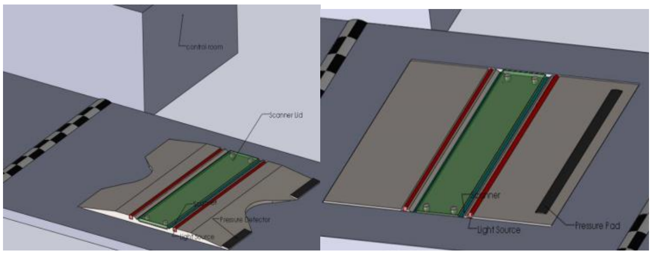


Figure 3 Proposed installations

References

[1] Sensors And Systems For The Detection Of Explosive Devices – An Overview. Metrol. Meas. Syst., Vol. Xix (2012), No. 1, Pp. 3-28

[2] Optimal Spatial Resolution In Vision-Based Inspetion Of Pipes Using Catadioptric Sensors, 2012 25th Ieee Canadian Conference On Electrical And Computer Engineering (Ccece) 978-1-4673-1433-6/12/$31.00 ©2012 Ieee

[3] SURF By H.Bay, A.Ess, T Tuyteleaars, L Van Gool –Computer Vision And Image..2008- Elsevier**....** Volume 110, Issue 3, June **2008**, Pages 346–359

[4] Automatic Image Stitching Using SIFT Yanfang Li, Yaming Wang, Wenqing Huang, Zuoli Zhang

[5] A Faster Image Registration And Stitching Algorithm By Chamindanamalsenarathne, Shanakaransiri, Pushpikaarangala, Asanka Dr. Chathura De Silva

[6] Medical Image Seamlessly Stitching By SIFT And GIST By Zhao Xiuyingandwanghongyu

[7]. Image Stitch Algorithm Based On SIFT And MVSC, 2010 Seventh International Conference On Fuzzy Systems And Knowledge Discovery (FSKD 2010)

[8] Exact Matching In Image Databases Peter Bosch, Alex Van Ballegooij, Arjen P. De Vries, Martin Kersten Center For Mathematics And Computer Science (CWI), Amsterdam, The Netherlands

[9] An Effective And Efficient Exact Match Retrieval Scheme For Symbolic Image Database Systems Based On Spatial Reasoning: A Logarithmic Search Time Approach P. Punitha And D.S. Guru

[10] A Fast Multiresolution Feature Matching Algorithm For Exhaustive Search In Large Image Databases. Byungcheol Song, Myung Jun Kim, And Jong Beom Ra.