

# Intelligent Electronic Surveillance Systems for Personal and Team Security in Public Places

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**Abstract:** Public security is of prime importance for establishing law and order in any society. With the advent of cheap and fast electronic systems, public security is prone to fall in the control of intruders. Whilst many electronic surveillance systems available in market claim to work effectively, their operation is questionable in crowded places where the subject under surveillance is occluded under clutter. Under such challenging task, computer vision techniques are very helpful which work on foreground segmentation of captured images to remove clutter. Further, images are preprocessed before applying many machine learning methods to log in the details of person behavior. Action recognition techniques are then used to detect unusual behavior which helps in personal security in public places.

**Index Terms:** Artificial intelligence, computer vision, database, descriptors, feature points, image processing, machine learning, optimization, electronic surveillance.

## I. INTRODUCTION

Electronic surveillance is a useful tool for personal security in public places. The electronic surveillance systems have a long history when large camera with analog processing of pictures were used to identify usual behaviors of subjects. With the advancement of sensor technology and high speed digital signal processors the task of surveillance has become quite useful and effective in places where earlier system failed. An approach to surveillance applicable to online extremism is studied in [1]. Analysis of electronic surveillance based on ground stations is given in [2]. Action analysis from video data is discussed in [3]. The paper also uses optical correlator for electronic surveillance. A radar electronic surveillance system is discussed in [4]. Electronic footprints have been used in surveillance in [5]. Personal security in public transport system is very important. In some routes on public transport at many places, passenger safety is a concern. A surveillance system in public transport is given in [6]. Accurate and precise sensors used in electronic surveillance system have a major role in overall performance of the system. A sensor based approach to electronic surveillance is discussed in [7]. While many applications need storage of video data for electronic surveillance applications, there is need for online surveillance in home environment for the safety of the people. An online home surveillance system is discussed in [8]. Frequency control and phase surveillance is discussed in [9]. A comparative study based on pulsed magnetic fields has been carried out in [10]. Modeling and simulation in ocean surveillance is

carried out in [11]. While the existing surveillance methods work effectively in many cases but in the presence of clutter, the surveillance becomes a challenging task. Following sections discuss the method os 2D feature descriptors towards electronic surveillance and discuss the role of 3D descriptors in robust surveillance systems.

## II. IMAGE FEATURE DESCRIPTORS

### A. Digital Image

A digital image is collection of pixels where each image pixel represents intensity of image at that position. A greyscale image of 8-bit represents intensity from 0-255 intensity levels where 0 represents black, 255 represents white whereas a value in between 0 to 255 represents a gray level. A digital image at position  $(x, y)$  can be represented as given in equation (1).

$$I(m, n) = A(x, y) \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(x - mX_s, y - nY_s) \quad (1)$$

Where  $I(m, n)$  represents pixel intensity at position  $(m, n)$ .

### B. Feature Points

Feature points, also known as interest points represent portions in an image where the neighborhood is characteristic of the feature point. A number of feature point detectors are available in image processing literature. Out of these methods, an appropriate feature point detection method is chosen depending on the brightness, outdoor or indoor environment, texture information etc.

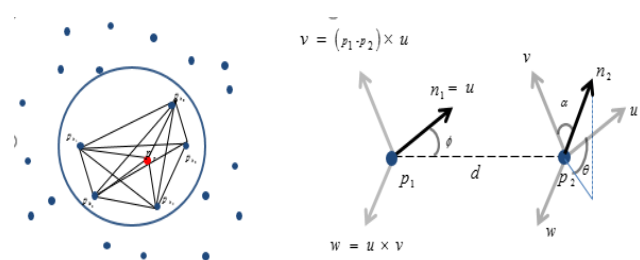


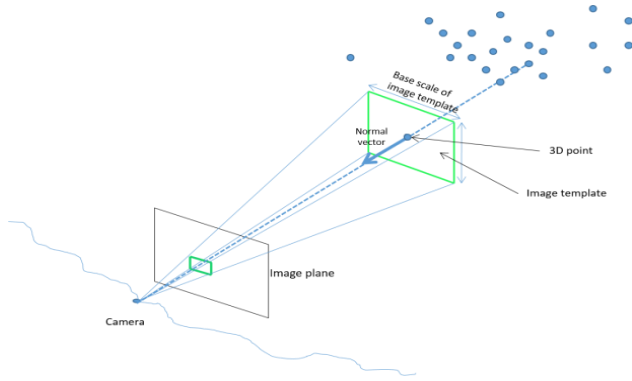
Figure 1. Descriptors based on point feature histograms.

## III. FEATURE VECTORS

Once feature points are detected with an appropriate feature point detector, the region around feature point is represented using a suitable descriptor. High dimensionally of the descriptor is preferred for effective matching, however the computation becomes expensive. PCA or sparse PCA is sometimes is used to dimensionality reduction of feature vectors.

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**Fig. 2. Projection of 3D point on image plane**

Image is obtained from the 3D scene using camera model. 3D points are projected on to the image plane using Epipolar geometry. The focal length of the camera, aperture size affects the image quality. Fig. 2. Show the projection of 3D point on image plane.

**A. Distance measurement**

Feature vectors are compared for two images using distance calculation.

*(i) Euclidean distance*

This distance is most widely used distance metric. Euclidean distance finds the distance between vectors of feature vectors of two images [9].

$$d = \sum_{i=0}^n |I_i^1 - I_i^2|^2 \quad (2)$$

*(ii) Canberra distance*

The feature vector distance is normalized by dividing the distance with sum of feature vectors magnitudes.

$$d = \sum_{i=0}^n \frac{|I_i^1 - I_i^2|}{|I_i^1| + |I_i^2|} \quad (3)$$

*(iii) Sum of Squared absolute distance (SSAD)*

This distance is sum of squares of difference between magnitudes of feature vectors of two images.

$$d = \sum_{i=0}^n (|I_i^1| - |I_i^2|)^2 \quad (4)$$

*(iv) Sum of absolute distance(SAD)*

This distance calculates sum of difference of absolute value of feature vectors of two images.

$$d = \sum_{i=0}^n |I_i^1| - |I_i^2| \quad (5)$$

*(v) Maximum value distance*

This distance is used to calculate the largest value of distance between feature vectors of two images.

$$d = \max(|I_1^1 - I_1^2|, |I_2^1 - I_2^2|, \dots, |I_n^1 - I_n^2|) \quad (6)$$

In descriptor matching, first match and second match is calculated. A match is discarded with the distance ratio of

first match to second match is more than 0.8.

**B. Outlier removal**

Feature vector in one image is compared those of in another image. It is sometimes a case when a feature point is wrongly matched to another feature point. In such a case, outlier removal methods are used to discard wrong matching of feature points.

**IV. DATABASE DESCRIPTORS**

A database of feature descriptors is constructed and is used to compare with that of the test image. A huge database of feature descriptors is stored along with position of each descriptor in the database.



**Figure 3. 2D image from database.**

**V. DEPTH AND INTENSITY MEASUREMENT**

2D image descriptors suffer from the drawback that these descriptors do not involve information about depth of the scene. 3D descriptors are used which store intensity as well as depth information in the database. A 3D camera which takes intensity and depth information of test image is used for robustness of the method.

In this step, depth information is estimated. Consider there are  $N_k^S$  frames in shot k. Then average pixel  $A(i, j)$  for shot k is given as below.

$$A(i, j) = \frac{1}{N_k^S} \sum_{i=1}^{S_k} p(i, j) \quad (7)$$

Average frame of shot k is computed for each pixel in the frame. The distance of each frame in shot k from the average frame is computed. A frame with minimum distance is selected as key frame for shot k and its depth information is estimated. Intensity of the image depends on lightening conditions whereas depth information is independent of variation in the lightening conditions.

**VI. RESULTS AND DISCUSSION**

3D scene is captured using a 3D camera where intensity as well as depth information is stored in computer. A database of 3D feature points along with their descriptors are stored. The scene under analysis is captured and their descriptors are matched with those in database. Fig. 1. Shows how descriptors are formed from a 3D scene. Descriptor matching is shown in Fig. 4.





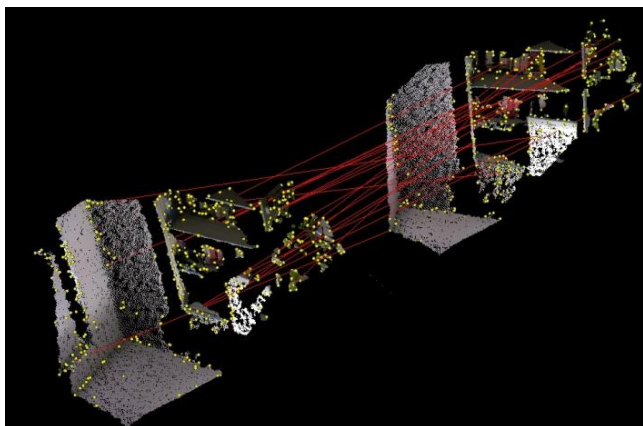


Figure 4. Descriptor matching of scene under analysis and of database.

3D descriptors are of large dimensions. The distance matching of two descriptors is highly computationally expensive. Instead of 3D descriptors, two descriptors are computed and distance is calculated using Euclidean distance. Fig. 5. Shows the descriptor matching in case of 2D images.

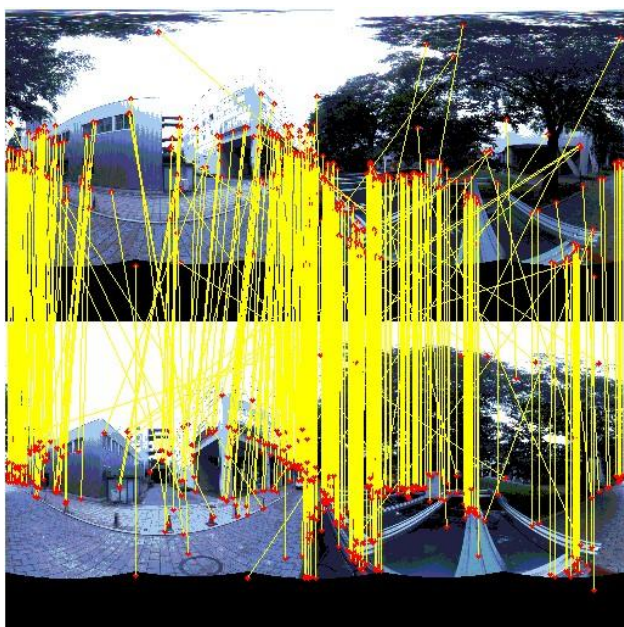


Figure 5. 2D matching of descriptors

It has been observed that outliers are negligible as compared to total number of correct matches which justifies the effectiveness of the method.

## VII. CONCLUSION

Electronic surveillance systems come in a variety of methods and designs, 3D descriptor based surveillance methods are robust to occlusion, clutter and outliers. These methods outperform their 2D counterparts where images are segmented and matched using 2D feature descriptors.

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## REFERENCES

1. M. Watney, "Intensifying State Surveillance of Electronic Communications: A Legal Solution in Addressing Extremism or Not?" Availability, Reliability and Security (ARES), 2015 10th International Conference on, Toulouse, 2015, pp. 367-373.
2. D. C. Andrew, "Ground stations for analysis of electronic surveillance imagery," Human Interfaces in Control Rooms, Cockpits and Command Centres, 1999. International Conference on, Bath, 1999, pp. 418-421.
3. C. Ovseník, J. Turán and A. K. Kolesárová, "Video surveillance systems with optical correlator," MIPRO, 2011 Proceedings of the 34th International Convention, Opatija, 2011, pp. 227-230.
4. M. Yaghoobi, B. Mulgrew and M. E. Davies, "An efficient implementation of the low-complexity multi-coset sub-Nyquist wideband radar electronic surveillance," Sensor Signal Processing for Defence (SSPD), 2014, Edinburgh, 2014, pp. 1-5.
5. J. Teng, J. Zhu, Boying Zhang, D. Xuan and Y. F. Zheng, "E-V: Efficient visual surveillance with electronic footprints," INFOCOM, 2012 Proceedings IEEE, Orlando, FL, 2012, pp. 109-117.
6. G. Elkana and I. Baskara Nugraha, "Low cost embedded surveillance for public transportation," ICT for Smart Society (ICISS), 2014 International Conference on, Bandung, 2014, pp. 242-245.
7. P. Pasupathy, S. Munukutla, D. P. Neikirk and S. L. Wood, "Versatile wireless sacrificial transducers for electronic structural surveillance sensors," Sensors, 2009 IEEE, Christchurch, 2009, pp. 979-983.
8. Z. B. May, "Real-time alert system for home surveillance," Control System, Computing and Engineering (ICCSCE), 2012 IEEE International Conference on, Penang, 2012, pp. 501-505.
9. V. M. López, A. Navarro-Crespín, C. Brañas, F. J. Azcondo, R. Schnell and R. Zane, "Frequency control and phase surveillance in resonant electronic ballast," IECON 2011 - 37th Annual Conference on IEEE Industrial Electronics Society, Melbourne, VIC, 2011, pp. 2929-2934.
10. Gang Kang and O. P. Gandhi, "Comparison of various safety guidelines for electronic article surveillance devices with pulsed magnetic fields," in IEEE Transactions on Biomedical Engineering, vol. 50, no. 1, pp. 107-113, Jan. 2003.
11. X. Pan and Y. Wu, "Modeling and simulations of ECCM of ocean surveillance satellite electronic intelligence," Biomedical Engineering and Informatics (BMEI), 2012 5th International Conference on, Chongqing, 2012, pp. 1476-1480.
12. M.J. Westoby, J. Brasington, N.F. Glasser, M.J. Hambrey, J.M. Reynolds, "Structure-from-Motion" photogrammetry: A low-cost, effective tool for geoscience applications, *Geomorphology*, Volume 179, 15 December 2012, Pages 300-314.
13. L. Zhao, S. Huang and G. Dissanayake, "Linear SLAM: A linear solution to the feature-based and pose graph SLAM based on submap joining," Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on, Tokyo, 2013, pp. 24-30.
14. Z. Kang and G. Medioni, "3D Urban Reconstruction from Wide Area Aerial Surveillance Video," Applications and Computer Vision Workshops (WACVW), 2015 IEEE Winter, Waikoloa, HI, 2015, pp. 28-35.
15. J. Ventura and T. Höllerer, "Wide-area scene mapping for mobile visual tracking," Mixed and Augmented Reality (ISMAR), 2012 IEEE International Symposium on, Atlanta, GA, 2012, pp. 3-12.
16. G. Bleser, H. Wuest and D. Stricker, "Online camera pose estimation in partially known and dynamic scenes," Mixed and Augmented Reality, 2006. ISMAR 2006. IEEE/ACM International Symposium on, Santa Barbara, CA, 2006, pp. 56-65.
17. T. J. Cham, A. Ciptadi, W. C. Tan, M. T. Pham and L. T. Chia, "Estimating camera pose from a single urban ground-view omnidirectional image and a 2D building outline map," Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on, San Francisco, CA, 2010, pp. 366-373.
18. M. Chatzigiorgaki and A. N. Skodras, "Real-time keyframe extraction towards video content identification," Digital Signal Processing, 2009 16th International Conference on, Santorini-Hellas, 2009, pp. 1-6.

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