

Visual Object of Tracking Humans at Night Based on Thermal Cameras

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ABSTRACT

Pedestrian safety on sidewalk of highways or residential street with heavy or light traffic conditions is a public concern. For security reasons, object tracking is needed as a form of supervision in improving pedestrian safety. Therefore, a thermal camera is needed to find out the position of objects such as humans, by applying object tracking devices at various points of view to monitor the environment. In order to identify objects such as humans in low light conditions, object tracking is carried out using tracking methods, namely Kernelized Correlation Filter (KCF), Support Vector Machines (SVM), and L1 Tracker Using Accelerated Proximal Gradient Approach (L1APG) based on a distance of 10 meters, 15 meters, 20 meters and the size of the object in the dataset. The results with 1684 image inputs showed that there is a good performance for each success plot distance in the SVM method of 99.25%, 99.75%, 98.74% as it can track successfully based on the object being tracked. The performance for each precision plot distance in the KCF method of 51.88%, 46.8%, 63.81% showed optimum and precisely accurate results for the object being tracked.

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1. INTRODUCTION

Pedestrian safety on sidewalk of highways or residential street with heavy or light traffic conditions is a public concern [1]. Pedestrians are also often the target of criminals such as theft, mugging, robbery, or accidents in a low light condition such as at night [1]. The number of pedestrian activities that occur on the side of the road makes a better security level is needed [2]. This creates demands for the development of visual-based security [3] that can work automatically so that scientists start creating various technologies and methods to meet these needs, as an example is the implementation of object tracking [4].

In object tracking, the object feature extraction process is very important because the characteristics obtained from an object will be used as comparisons for the tracking process [4][6]. The object is a pedestrian which is carried out using thermal camera technology [4][6]. As a solution for monitoring and improving pedestrian safety, it is necessary to install thermal camera devices [5] at various viewing angles that can be applied to monitor the environment [3]. With a thermal camera, it is expected to provide pedestrian tracking information, such as an orientation of motion, area, or shape of an object [5].

In the study that was conducted by Qiao Liu and Zhenyu He, pedestrian tracking was carried out using a dataset that included 60 thermal sequences and then applied to 9 tracking methods. However, this design is less efficient because it does not mention the distance in the dataset used and uses different dataset resolutions [3].

Based on the research that has been done, the authors compared 1 object in the dataset that has been created using a thermal camera with same resolution. The object used was a human walking on foot at night. The object tracking dataset used has 3 different distances, and comparisons are made with 3 tracking methods, namely Kernelized Correlation Filter (KCF) [7], Support Vector Machines (SVM) [8], and L1 Tracker Using Accelerated Proximal Gradient Approach (L1APG) [9] to see the results of a good tracking method in clarifying objects.

The contribution of this research is to compare several visual tracking methods to the thermal video dataset that will be taken at night. The authors created a sequential thermal image dataset that was focused on occlusion conditions to be used as a reference for testing the tracking system's performance in overcoming objects that are in long-term occlusion.

2. METHODS

2.1 KCF Method

KCF or Kernelized Correlation Filters is a classic tracking algorithm that has existed in recent years. It is a benchmark algorithm for many tracking filter algorithms [7]. KCF tracks objects based on Kernel based tracking that has high processing speed and is superior to track objects in real time. KCF has good performance on tracking without high computational power compared to other methods [7][10].

KCF has a high tracking rate, if there are no obstacles between the camera and the desired area. However, if there are obstacles that cover the target area, it will result in losing objects and tracking other object areas [4].

2.2 SVM Method

SVM or Support Vector Machine is a classic binary classification algorithm. SVM method can effectively distinguish negative and positive samples [11][13]. In a binary classification task, the goal is to find the optimal separating hyper-plane. Hyper-plane with maximum margin will give better generalization on classification method. Margin is the distance between the hyper-plane and the closest data from each class. The data vectors closest to the dotted line in the transformed space are called Support Vector (SV) [11] [12].

Figure 1 shows a two-class problem with many possible hyper-planes separating the two data sets, +1 and -1. Data belonging to class -1 is symbolized by a square shape, while data in class +1 is symbolized by a circle [12]. In Figure 2, the optimal separating hyper-plane (OSH) results in the maximum margin (dashed line) between the two data sets. The image on the right shows the best hyper-plane, which is located right in the middle of the two classes, while the data of circles and squares that are crossed by the margin line (dotted line) are support vectors [12].

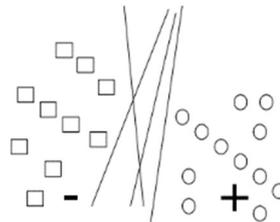


Figure 1. The Splitting Hyper-plane that Divides the Two Groups [12]

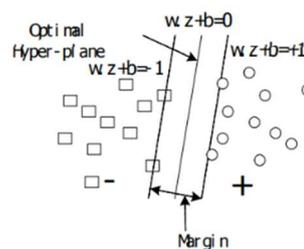


Figure 2. Optimal Splitting Hyper-Plane and Maximum Margin [12]

2.3 L1APG Method

The L1APG method is closely related to the shortcomings of the L1 tracker method [15]. The main differences between the two methods are different minimization models and a much faster numerical solver for the resulting L1 minimization problem. L1APG is used to minimize the sum, while the APG method is used to solve unrestricted problems related to L1 namely image restoration [14] then reduce computational costs and make the tracking algorithm real time, although tracking in this method shows good performance by using trivial templates, the tracking process can be generalized better [16].

2.4 System Design

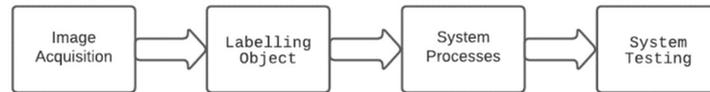


Figure 3. Block Diagram

The system uses 3 tracking methods, namely KCF, SVM and L1APG which will then classify the thermal image.

Figure 3 explains the design of the research system that has several stages. The first stage is the image input from the thermal camera which is then continued by the object labeling process that is carried out using labeling software. Objects that are labeled are objects with short bodies. After that, the tracking process is designed using the KCF, SVM and L1APG methods. The results obtained are then tested to obtain good success plot and precision plot results from the three methods.

2.5 Image Acquisition

Image acquisition in this study uses images taken using the Android version of the FLIR ONE Gen 3 camera with Thermal Resolution 80x60, Thermal sensor Pixel size 17 μ m, 8 – 14 m spectral range, Video and still Image Display/Capture Saved 640x840. The results are in the form of videos which are then captured into RGB image pieces in JPG file format. There are 1684 images in total, consisting of 533 images for a distance of 10 meters, 672 images for a distance of 15 meters, and 479 images for a distance of 20 meters. Figure 4 is an example of the results of the dataset with a FLIR ONE Gen 3 camera for each distance.

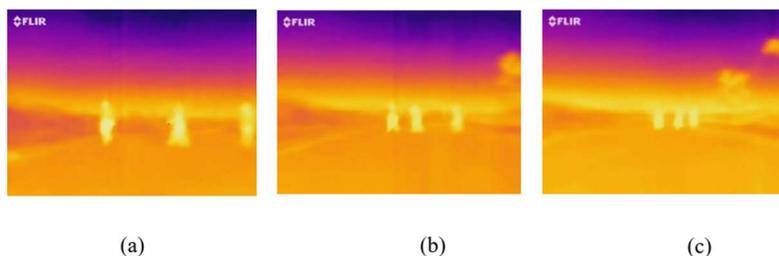


Figure 4. Thermal image distances of 10 m (a), 15 m (b), 20 m (c)

2.6 Labeling Image

Labeling is part of the process of this research to provide a label in detecting an object of an image. The image consists of 3 objects which are then labeled on the object to be detected, namely a short object. Objects in the image are detected using the labeling application.

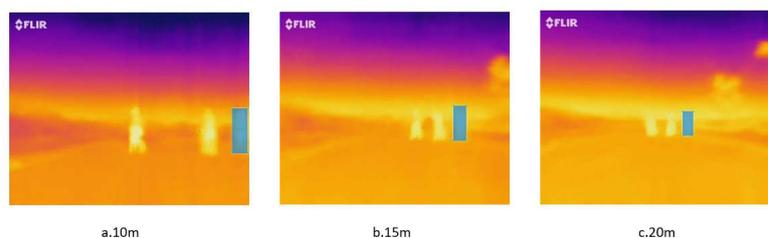


Figure 5. Labeling Image Results

The image data that has been labeled then goes to the pre-processing stage. The detected image stages then produce an output file format in the form of an XML document. The value contained in the output XML document is converted into a TXT file format. All data at each distance is combined into one TXT file so that

it can be processed according to the provisions of each method. The results of the TXT output at each distance can be seen in Figure 6

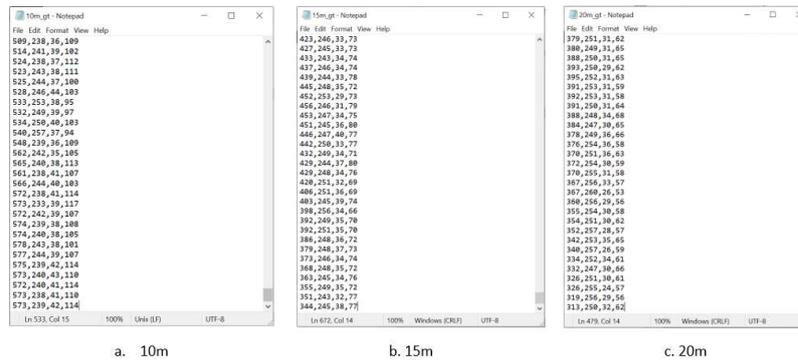


Figure 6. TXT file of each distance

2.7 Performance Test Parameters

1. Success Plot

Success plot is a parameter that evaluates object tracking or object tracking based on overlap scores [3]. Suppose that the bounding box of the object being tracked is $r(t)$ and the bounding box groundtruth is represented as r_0 , then the overlap score is defined as follows [4]:

$$s = \frac{r(t) \cap r_0}{r(t) \cup r_0} \times 100\% \quad (1)$$

With \cap and \cup are intersections and combinations, while s indicates the number of pixels in an area. The average of the overlap scores or often referred to as the Average Overlap Score (AOS) can be used as a measure of performance. The overlap score can be used to determine whether an algorithm tracks successfully or not on a frame, by testing whether s is greater than the threshold. The success plot test is carried out on each method of KCF, SVM, and L1APG with short objects at a distance of 10 meters, 15 meters, and 20 meters.

2. Precision Plot

Precision plot is a parameter used to evaluate object tracking based on center location error [3]. The precision plot calculates the average Euclidean distance between the center location of the tracking target object and the ground-truth center position of each frame. The percentage of frames whose location estimates are given a threshold distance from ground-truth is a better performance measurement than without a threshold distance from ground-truth. Center location error only calculates the difference and does not pay attention to the size and scale of the target object [4]. Equation 2.2 is the formula used to calculate the distance between the ground-truth bounding box centroid and the bounding box tracker.

$$J_c = \sqrt{(x_t - x_g)^2 + (y_t - y_g)^2} \quad (2)$$

with J_c is the centroid distance, x_t and y_t are the x, y centroid points on the bounding box tracker, x_g and y_g are the x, y centroid points on the ground-truth bounding box. This precision plot test is carried out on each method, namely KCF, SVM, and L1APG with short objects at a distance of 10 meters, 15 meters, and 20 meters.

3. RESULTS AND DISCUSSION

This chapter contains the results of system testing that had been carried out for object tracking detection using a thermal camera using the KCF, SVM, and L1APG methods. The analysis was carried out on short objects with different distances, namely 10 meters, 15 meters, and 20 meters.

3.1 Method testing scenarios

3.1.1 Method Success plot results

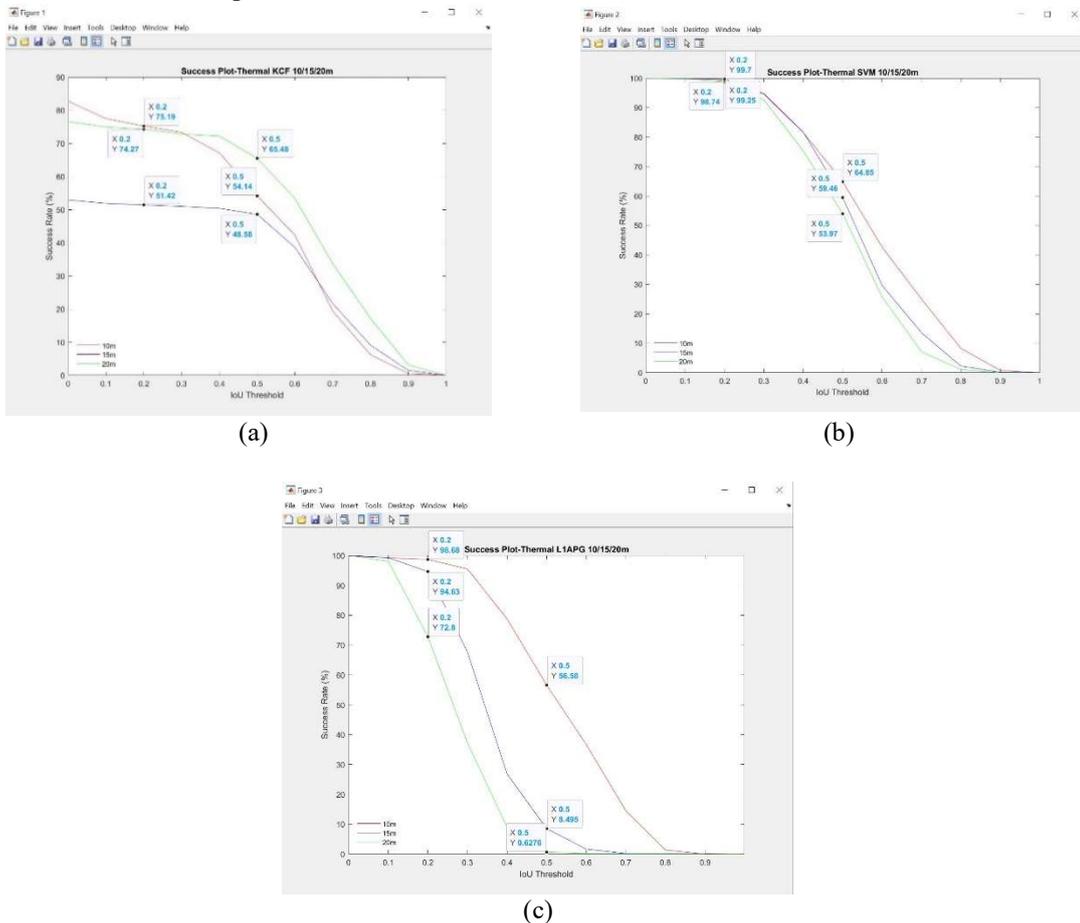


Figure 7. Success Plot Methods KCF (a), SVM (b), L1APG (c)

Figure 7 is a graphic result of the success plots of all methods, namely KCF (a), SVM (b), and L1APG (c). For the success plot parameters, IoU thresholds of 0.2 and 0.5 were used because these values are the actual values for detecting the bounding box results. The KCF method (a) has a good success plot at a distance of 10 meters, which is 75.19%, while at other distances the detection results are said to be not optimal because this method is not influenced by distance but obstacles to the object. The SVM method (b) gets the actual success plot at a distance of 20 meters, which is 98.74%. The performance of this method is very good in detecting the object needed and is not affected by distance. For the L1APG method (c) the results of a good success plot at a distance of 10 meters are 98.68% and this method has a success plot that is influenced by the distance of the object. The farther away the object, the harder this method to detect.

3.1.2 Method precision plot results

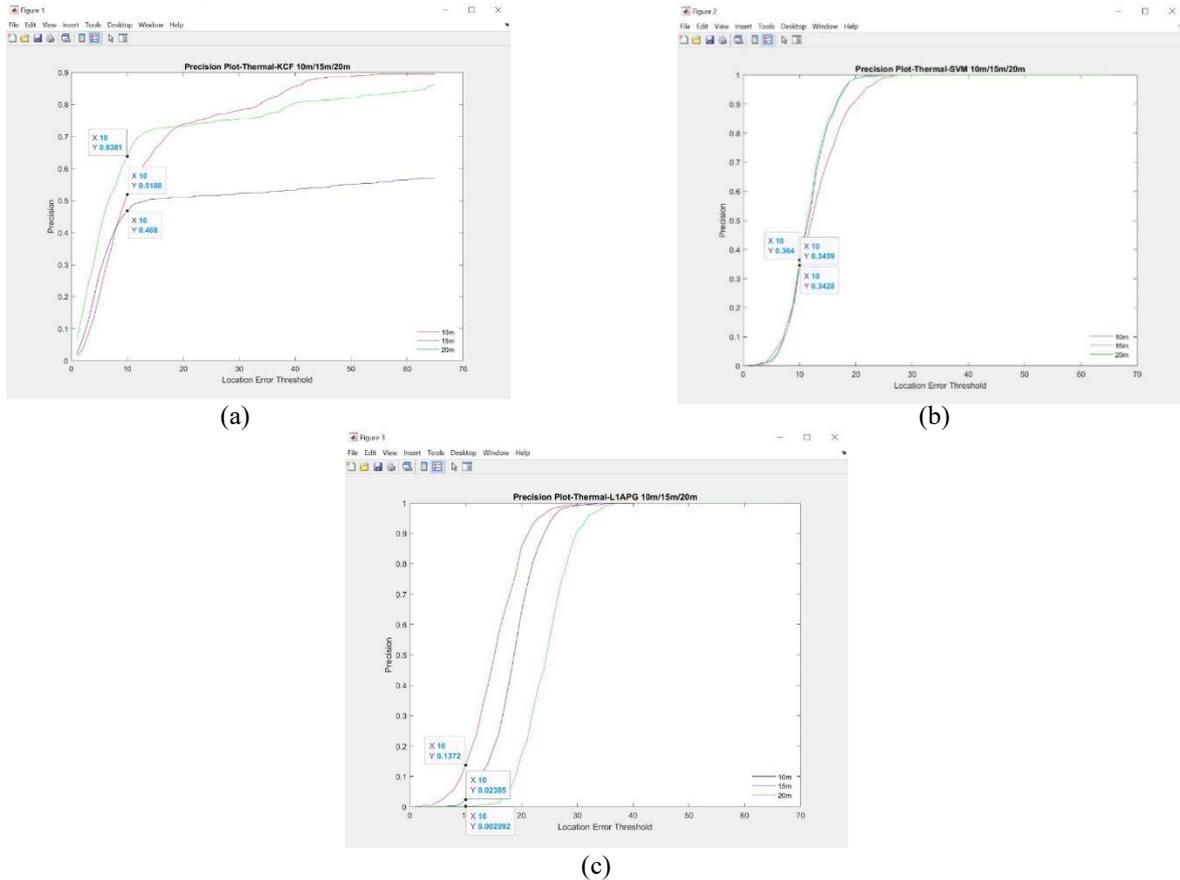


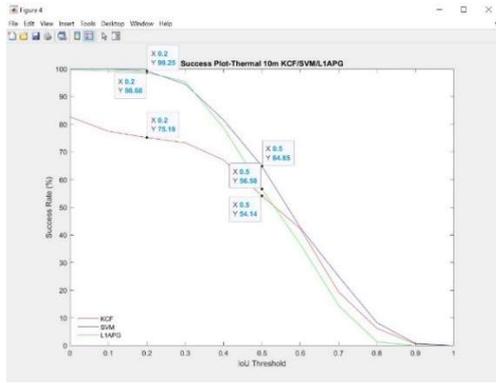
Figure 8. Precision Plot Methods KCF (a), SVM (b), L1APG (c)

Figure 8 is a graphic result of the precision plots of all KCF (a), SVM (b), L1APG (c) methods. Precision plot performance where the location error threshold is 10 in the KCF method (a) good precision results are obtained at a distance of 20 meters, which is 63.81%, for the SVM method (b) a good precision performance is obtained at a distance of 20 meters, which is 36.4%, and in the L1APG method. (c) A good precision performance is obtained at a distance of 10 meters by 13.72%. Precision for the L1APG method is affected by object distance while it is not affected for KCF and SVM.

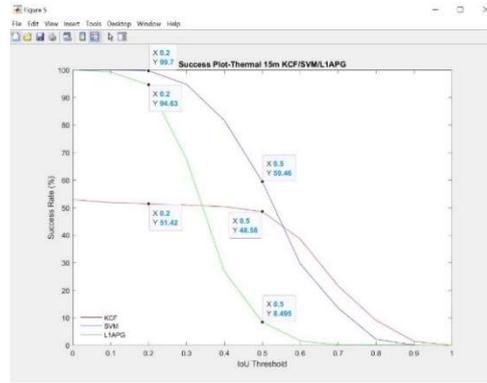
3.2 Distance Testing Scenario

3.2.1 Success Plot Results distance

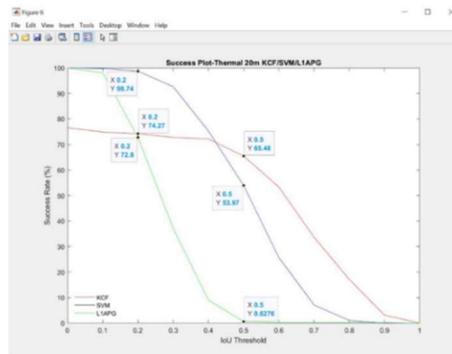
Figure 9 is a graphic result of the success plot for each distance, 10 meters (a), 15 meters (b), and 20 meters (c). At a distance of 10 meters, the result (a) has a good success plot result, the L1APG method is 98.68%, while in other methods the results of the detection at a distance of 10 meters can be said to be good and in accordance with the detected object. At a distance distance of 15 meters, it (b) gets the actual success plot results in the SVM method, which is 99.7% performance at this distance looks different in each method and has a success plot that is not good at detecting the objects needed in the KCF method. For a distance of 20 meters, (c) the results of a good success plot on the SVM method, namely 98.74% have a good success plot compared to other methods.



(a)



(b)



(c)

Figure 9. Success Plot Distance 10m (a), 15m (b), 20m (c)

3.2.2 Precision Plot Results distance

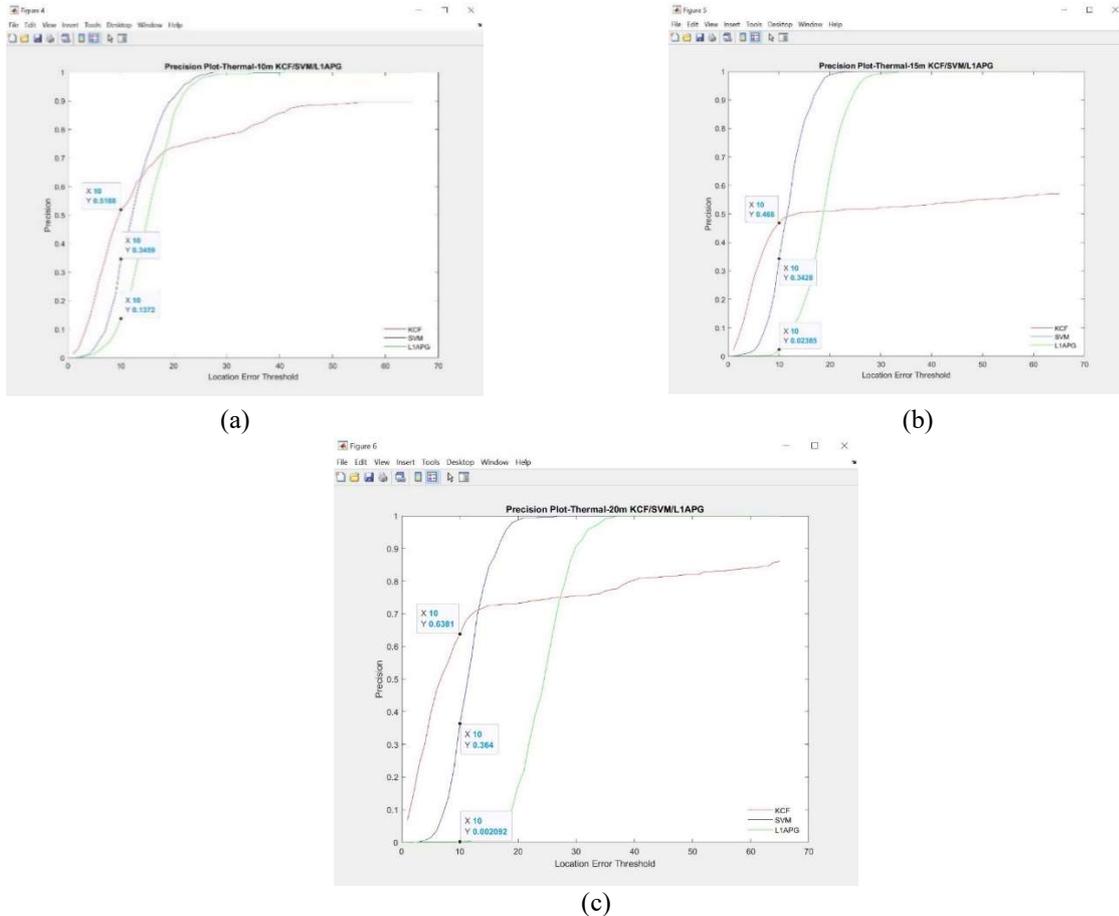


Figure 10. Precision Plot Distance 10m (a), 15m (b), 20m (c)

Figure 10 is a graph of the precision plot for all distances of 10 meters (a), 15 meters (b), and 20 meters (c). The precision plot performance in detecting objects where the location error threshold is 10 at a distance of 10 meters (a) a good precision result is obtained by the KCF method, namely 51.88%, for a distance of 15 meters (b) a good precision performance is obtained by the KCF method, which is 46.8%, and at a distance of 20 meters (c) a good precision performance on the KCF method is 63.81%. The precision performance for the KCF method is better and more accurate in detecting the appropriate object in the image compared to the SVM and L1APG method.

3.3 Analysis of Distance Systems and Methods

After getting all the graph results for the success plot and precision plot for each method and distance, the results of the analysis related to the tracking method and the distance of the detected object will be carried out, as well as the speed of each method in detecting the required object.

3.3.1 Success Plot Method and Distance

Table 1. Success Plot Results

Metode	KCF		SVM		L1APG	
	IoU		IoU		IoU	
Jarak	0.2	0.5	0.2	0.5	0.2	0.5
10 Meter	75.19%	54.14%	99.25%	64.85%	98.68%	56.58%
15 Meter	51.42%	48.58%	99.7%	59.46%	94.63%	8.495%
20 Meter	74.27%	65.48%	98.74%	53.97%	72.80%	0.6276%

Table 1 the overall results of success plots for all methods and all distances. The success plot performance of the SVM method has the best, actual, and dominant performance accuracy results because it can be seen from the detection performance and can detect objects in the image well. The KCF method has poor performance results because this method cannot detect objects if the object is exposed to obstacles. Meanwhile, the L1APG method has good performance on object distance parameters, the farther the distance, the object is more difficult to be detected.

3.3.2 Precision Plot Method and Distance

Table 2. Precision Plot Results

Metode	KCF	SVM	L1APG
LET			
Jarak	10	10	10
10 Meter	51.88%	34.59%	13.72%
15 Meter	46.8%	34.28%	2.385%
20 Meter	63.81%	36.4%	0.2092%

Table 2 shows the overall results of precision plots for all methods and all distances. The best precision performance is the KCF method for all distances with a location error threshold of 10. The KCF method has the best precision value, this can be seen from the visualization that shows the results of the detected object according to the object needed, namely a short human, and for the SVM method has better precision performance than the L1APG method. The SVM method has poor accuracy because the detection is not optimal for objects, and the L1APG method has poor accuracy because the detection is affected by distance.

3.4 Tracking Speed Comparison

Table 3. FPS Method

Metode	KCF	SVM	L1APG
Jarak			
10 Meter	193.41	162.26	102.7351
15 Meter	184.99	162.45	96.5702
20 Meter	261.14	224.93	46.7961

Table 3 shows a comparison of the average tracking speed (frames per second) of the 3 methods, which are KCF, SVM, and L1APG based on distance. It can be seen in table 3 that the KCF method has a high speed in detecting objects in the frame for each distance, then continued with the speed of the SVM method. Both methods have the fastest performance capability in detecting each frame in real time. In addition, the L1APG method has the lowest speed and takes time to detect objects for each frame in real time. This method has good detection results but lacks precision.

4. CONCLUSION

From the results of the analysis and testing that has been carried out based on object tracking on the KCF, SVM and L1APG methods, the conclusion of this study is that the system designed for object tracking with the KCF, SVM and L1APG methods has been successfully carried out within the distances of 10 meters, 15 meters, and 20 meters. The best object tracking system performance based on the success plot was obtained in the SVM method for IoU threshold 0.2 for a distance of 10 meters by 99.25%, a distance of 15 meters by 99.75%, and a distance of 20 meters by 98.74%. Meanwhile, the best object tracking system performance based on a precision plot with a location error threshold of 10 was obtained in the KCF method at a distance of 10 meters by 51.88%, a distance of 15 meters by 46.8%, and a distance of 20 meters by 63.81%.

Suggestions that can be made to improve the results of this study are to replace the input image dataset by using another type of thermal camera, and to use a longer duration video input so that the performance results obtained can be seen.

REFERENCES

- [1] P. Stoker, A. Garfinkel-Castro, M. Khayesi, W. Odero, M. N. Mwangi, M. Peden, and R. Ewing, "Pedestrian Safety and the Built Environment: A Review of the Risk Factors," *Journal of Planning Literature 1-16*, doi: 10.1177/0885412215595438.

- [2] A. Nowosielski, K. Malecki, P. Forczmański, A. Smoliński, and K. Krzywicki, "Embedded Night-Vision System for Pedestrian Detection," *IEEE Sensors Journal*, vol. 20, no. 16, pp. 9293-9304, doi: 10.1109/JSEN.2020.2986855
- [3] Q. Liu, Z. He, X. Li, and Y. Zheng, "PTB-TIR: A Thermal Infrared Pedestrian Tracking Benchmark," *IEEE Trans. Multimed.*, vol. 22, no. 3, pp. 666-675, 2020, doi: 10.1109/TMM.2019.2932615.
- [4] Y. Wu, J. Lim, M. Yang, "Online Object Tracking: A Benchmark," 2013, *IEEE Conference on Computer Vision and Pattern Recognition*, doi: 10.1109/CVPR.2013.312
- [5] W. K. Wong, P. N. Tan, C. K. Loo, and W. S. Lim, "An Effective Surveillance System Using Thermal Camera," *2009 international conference on signal acquisition and processing*, pp. 13-17. IEEE, doi: 10.1109/ICSAP.2009.12.
- [6] Yilmaz, A., Javed, O., dan Shah, M., (2006). "Object Tracking: A Survey, ACM Computing Surveys". Vol. 38 No. 4, Article 13, doi: 10.1145/1177352.1177355
- [7] B. Shilei, T. Xijun, Z. Jiaxin, "Research on Object Tracking Algorithm Based on KCF," 2020 *International Conference on Culture-oriented Science & Technology (ICCST)*, doi: 10.1109/ICCST50977.2020.00055.
- [8] Supreeth, H. S. G., and C. M. Patil, "An Adaptive SVM Technique for Object Tracking," *International Journal of Pure and Applied Mathematics*, Volume 118 No. 7 2018, 131-135, ISSN: 1314-3395.
- [9] C. Bao, Y. Wiu, H. Ling, and H. Ji, "Real Time Robust L1 Tracker Using Accelerated Proximal Gradient Approach," *2012 IEEE Conference on Computer Vision and Pattern Recognition*, doi: 10.1109/CVPR.2012.6247881.
- [10] W. Qiang, Z. Zhou, "Long-term Tracking Based on Kernelized Correlation Filtering," 2018, *International Conference on Network and Information Systems for Computers*, doi: 10.1109/ICNISC.2018.00041
- [11] H. Tao, X. Shen, Q. Deng, "Infrared Target Tracking Algorithm Based on Bernaolli Filter and Support Vector Machine," 2020, *International Conference on Information Science and Education (ICISE-IE)*, doi: 10.1109/ICISE51755.2020.00067.
- [12] H. Song, Mei-li Shen, "A Specific Target Track Method Based on SVM and AdaBoost," 2008, *International Symposium on Computer Science and Computational Technology*, doi: 10.1109/ISCSCCT.2008.13.
- [13] Rajasekhar Nannapaneni, "Machine Learning-Based Object Tracking," 2019, Sr Principal Engineer, Solutions Architect, Dell Technologies
- [14] Z. Shen, K. Toh, and S. Yun, "An Accelerated Proximal Gradient Algorithm for Frame-Based Image Restorations via the Balanced Approach," 2011, *SIAM J on Imag. Sci.*, doi: 10.1137/090779437
- [15] C. Bao, Y. Wiu, H. Ling, and H. Ji, "Real Time Robust L1 Tracker Using Accelerated Proximal Gradient Approach," 2012, IEEE, doi: 10.1109/CVPR.2012.6247881
- [16] Shan. Jiang, Xiaoqiang. DI, "An Efficient Misalignment Method for Visual Tracking Based on Sparse Representation," *IEICE TRANSACTIONS on Information and Systems*, Vol.E101-D, No.8, pp.2123-2131, doi: 10.1587/transinf.2018EDP7052.
- [17] M. A. H. Baso, "Peningkatan Performansi Kernel-Based Object Tracking Menggunakan Type-2 Fuzzy Logic," 2019, Universitas Telkom, Bandung
- [18] J. Park, S. Kim, and Y. Lee, "Improvement of the KCF Tracking Algorithm through Object Detection," 2012, *International Journal of Engineering & Technology*
- [19] F. Joao, Henriques, R. Caseiro, P. Martins, and J. Batista, "High-Speed Tracking with Kernelized Correlation Filters," 2015, *IEEE Transactions On Pattern Analysis And Machine Intelligence*, doi: 10.1109/TPAMI.2014.2345390
- [21] J. S. Kulchandani, K. J. Dangarwala, "Moving Object Detection: Review of Recent Research Trends," 2015, *International Conference on Pervasive Computing (ICPC)*, doi: 10.1109/PERVASIVE.2015.7087138