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Tagged Grid Matching Based Object Detection in Wavelet Neural Network

R. Arulmurugan, P. Sengottuvelan

***Abstract*—**Object detection using Wavelet Neural Network (WNN) plays a major contribution in the analysis of image processing. Existing cluster-based algorithm for co-saliency object detection performs the work on the multiple images. The co-saliency detection results are not desirable to handle the multi scale image objects in WNN. Existing Super Resolution (SR) scheme for landmark images identifies the corresponding regions in the images and reduces the mismatching rate. But the Structure-aware matching criterion is not paying attention to detect multiple regions in SR images and fail to enhance the result percentage of object detection. To detect the objects in the high-resolution remote sensing images, Tagged Grid Matching (TGM) technique is proposed in this paper. TGM technique consists of the three main components such as object determination, object searching and object verification in WNN. Initially, object determination in TGM technique specifies the position and size of objects in the current image. The specification of the position and size using the hierarchical grid easily determines the multiple objects. Second component, object searching in TGM technique is carried out using the cross-point searching. The cross out searching point of the objects is selected to faster the searching process and reduces the detection time. Final component performs the object verification process in TGM technique for identifying (i.e.,) detecting the dissimilarity of objects in the current frame. The verification process matches the search result grid points with the stored grid points to easily detect the objects using the Gabor wavelet Transform. The implementation of TGM technique offers a significant improvement on the multi-object detection rate, processing time, precision factor and detection accuracy level.

***Keywords*—**Object Detection, Cross-point Searching, Wavelet Neural Network, Object Determination, Gabor Wavelet Transform, Tagged Grid Matching.

I. Introduction

OBJECT detection is in top hierarchy for solving the different computational problem. The object detection on the 2-D characteristic views is a difficult problem for the operator to recognize the images because the computer lacks in providing the adaptive learning. The inductive processes represent the common and professional means for extracting and encoding the relevant images from the environment. The development of WNN intelligence act as a result of interactions within the image processing environment. The object recognition revolves around the all levels of learning process to easily detect the objects.

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Contextual Object Localization as explained in [6] combines the pixel and image area connections with appearance features. Feature applies a restricted arbitrary field which incorporates the object level interactions. By learning a single space, a nearest neighbor prediction is optimized and able to quantitatively compare the contributions. The nearest neighbor on each base feature descriptor is measured up to the learned space level. Linear classifier as represented in [16] decides the target from the backdrop image and performs online reports with larger dissimilarity of time. The object representation by sparse coding and multi-scale max pooling is not created in linear classifier to acquire prior information about the image.

A special tree is to formalize the feature subset space as illustrated in [12] which is used to evaluate the feature subset but efficient greedy search algorithm is not developed. The algorithm is not developed, so that the search tree is not obtained with optimal k-feature subset. The global optimal k-feature subset fails to decide 'k' features repeatedly. The drift problem still occurs in the greedy search algorithm. Evolution Constructed (ECO) features as demonstrated in [14] build features to rely and work on the person's information.ECO routinely constructed to employ the normal genetic algorithm for discovering the transforms.

On-line Discriminative Tracking Feature Selection as described in [17] support pattern recognition and multi-target tracking. Eventually, gets a reliable multi-object tracking results while following the feature selection. A motion model of the target unites discovery and probability reference method to get better the performance of tracking tasks.

Synthetic posture generation scheme as described in [7] expand the group of postures and decrease the result on inadequate postures. Virtual contour constructions are not created adequately but shift occurs nonlinearly throughout an occlusion period. Synthetic posture generation scheme does not deal with the elucidation transform problem. Finally, the synthetic posture generation method fails to deal with objects which clearly decomposed into constituent components.

The WNN is measured as a prolonged perception in which the neurons of the initial layer are replaced by wavelet nodes. The wavelet nodes permit the detection of the transient as well as collection of little amount significant features. The features include the size, color and texture of the image. The motive for the application of WNN is that the feature extraction and representation properties of the wavelet transform are merged into the structure of the ANN to further expand the capability to estimated complicated patterns. The features observe as inputs to the following neurons used as a classifier.

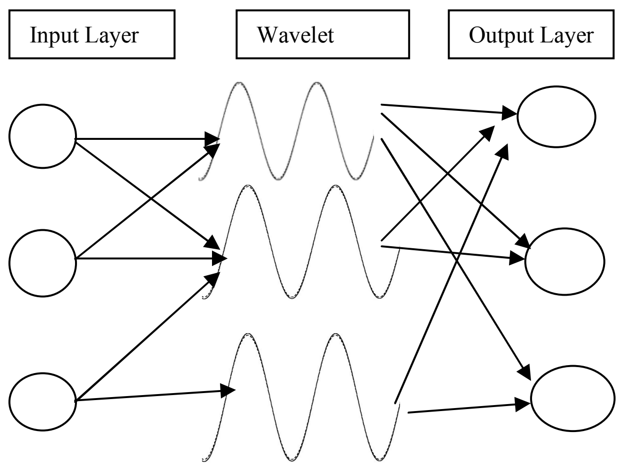

Fig. 1 Wavelet Neural Network Diagrammatic form

The WNN designed in Fig 1 using the three layer arrangement with an input layer, a wavelet layer, and an output layer. The topological arrangement of the WNN contains the hidden neutrons in the wavelet layer with different resolutions. Wavelet Neural Network concept is used for image processing which seems to be very efficient. WNN structure offers the parallel processing of images and training process makes the network suitable for the various kind of image processing.

Lightweight Detection as demonstrated in [5] provides priori requirements and assumed as a basis for the derivation of each detector. Neither ML inference nor the approximations lead to the most favorable detection performance over a set of test images but parameter estimation process creates a computational bottleneck. Conditional Random Field (CRF) model considers unary component properties and binary background module. The both relationships with supervised factor in [9] are examined. In conclusion, text components are grouped into content outline with a learning-based energy minimization method.

Adaptive Reflection Detection Using Computational Intelligence Techniques in [13] has set of features which measured from the iris image effectively. Computational intelligence is used to achieve an exact recognition of the reflection position using a trained classifier. In addition, Radial Symmetry Transform (RST) recognizes the reflections in iris images. A Bayesian algorithm as demonstrated in [18] produces the joint nonlinear un-mixing and nonlinearity detection algorithm. The pure component spectra fail to demonstrate jointly with the abundance estimation and the nonlinearity detection.

Cluster-based algorithm for co-saliency detection as illustrated in [1] communicates between the multiple images and the clustering process. The image attention is provided to the contrast, spatial, and cluster saliency. The ultimate co-saliency maps combine the particular image saliency and multi-image saliency for successful detection method. Existing co-saliency object detection performs the work on the multiple images but not desirable to handle the multi scale image objects in WNN.

In this work, focus is made on developing the Tagged Grid Matching technique with three components. Initial component TGM technique works to determine the object position and size. The quad tree is used to determine the position and size of the multiple objects. The determination of objects position and size in the WNN, second component works on to identify the objects. The cross out searching point easily identifies the objects with the cross outline checking. The cross outline checks the eight neighboring pixel (i.e.,) in square shape for the faster searching process. Final component is to perform the matching operations to identify the accuracy level. The Gabor wavelet transform easily detect the objects on the high resolution remote sensing image.

The structure of this paper is as follows. In Section I, describes the basic problems in multi-object detection and existing work limitations. In Section III, present an overall view of the Tagged Grid Matching (TGM) technique. The sub sections are object determination, object searching and object verification. Sections III and IV outline experiment results on Wilt Data Set with parametric factors and present the result graph for research questions. Section V describes about related work. Finally, Section VI concludes the work with better object isolation through matching technique

II. Tagged Grid Matching Technique Based Object Detection in Wavelet Neural Network

In Tagged Grid Matching technique the current objects are matched with the stored objects for the easy detection of the objects in the high-resolution remote sensing images. The each object in the current image is searched using the cross out grid points for the best detection result. The matching criterion uses the object determination, object searching and verification process for the object detection process. The object matching initially subtracts the background images for the extensive use in detecting objects. Fig. 2 illustrates the Tagged Grid Matching (TGM) technique on the high resolution remote sensing image with three components.

Fig. 2 describes the overall flow diagram of the Tagged Grid Matching technique. High resolution remote sensing images are divided into frames. The TGM technique is then divided into three components. The first component is the object determination based on the position and size. The position and size of the each frame is determined using the hierarchical grid points. The hierarchical grid points are introduced in TGM technique to improve the position and size determination on the multiple objects.

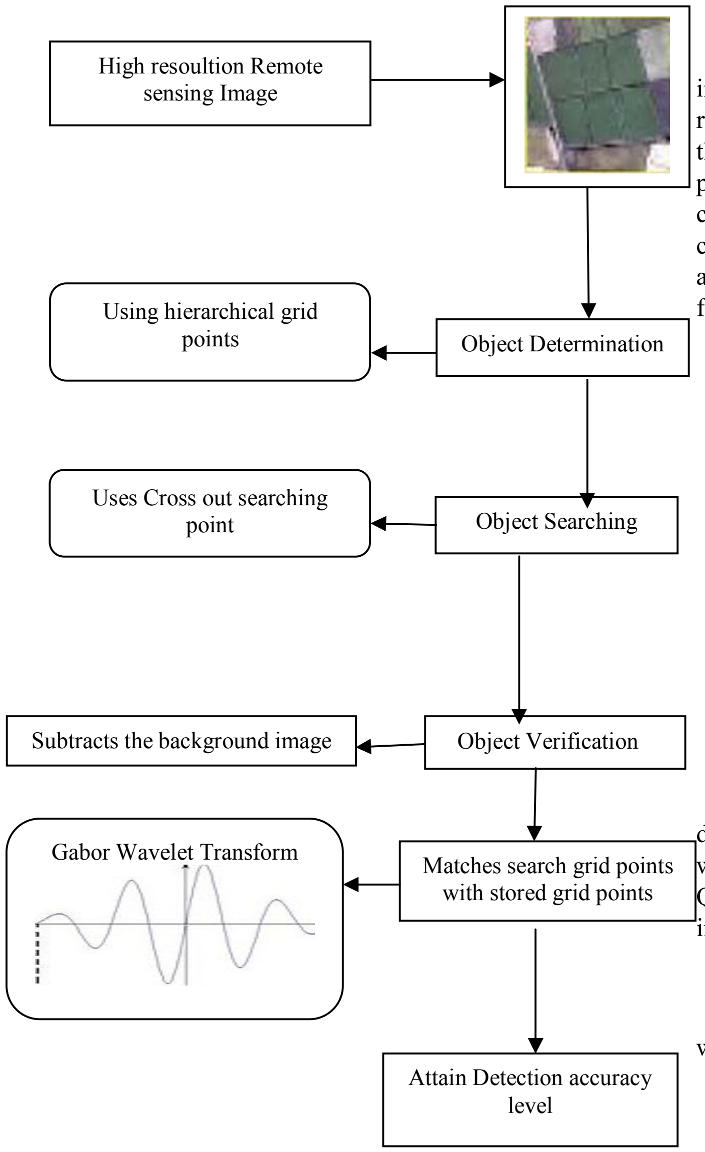

Fig. 2 Flow Diagram of Tagged Grid Matching Technique

The second component is the object searching in the high resolution remote sensing images for identification of the objects. The cross out searching point is developed in TGM technique which reduces the processing time. Cross out searching point carried out the larger area and object searching performs in faster way. Cross out searching point in TGM technique takes the four points in the square shape and perform the computation process. The computation process on remote sensing images produce faster search results, else the subtraction of the background image take place.

Finally, the last component object verification is carried out with matching process. The matching takes place between the search grid point result and the stored grid point results. If matched with high accuracy, then the objects are detected. The subtraction process removes all the background disturbances and performs the Gabor Wavelet Transform. The Gabor wavelet transform is performed to improve the matching and attain the accuracy level while detecting the objects.

A. TGA Object Determination

The TGA hierarchical grid points are used to partition the images into the mutual disjoint regions. The mutual disjoint regions help to cover all the pixels in the image and determine their position and size of the objects. The hierarchical grid point follows the Quad tree where each node (i.e.,) object 'o' corresponds to the cell in the Quad tree. The node communicates to the unit square in the Quad tree with objects and Quad tree has the four cells on each square form. In TGM, four cells in Quad tree represent the equal sized squares.

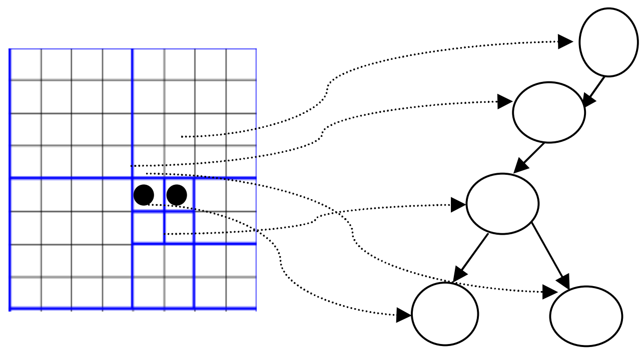

Fig. 3 Quad Tree Representation with Labeled Grid point Matching

Fig. 3 represents the Quad Tree which is used for the object determination in the image. The object are denoted as node in wavelet neural network and represented in 'o' with depth'd' in Quad tree. The quad tree based object position determination in image is uniquely defined as,

$$\text{Object Position \&size} = (\text{length }(O), (x, r), (y, r)) \tag{1}$$

where,

length (o) –Length of the object in the image

(x, r) – The x is the horizontal grid point of radius 'r'

(y, r) – The y is the vertical grid points of radius 'r'

Quad tree with hierarchical grid points handles the multiple object determination and formulated as,

$$\text{Set of objects (o)} = \frac{\max_{i,j \in Gridpoints} |i-j|}{\min_{i,j \in Gridpoints} |i-j|} \tag{2}$$

The quad tree in the WNN contains the multiple objects in the image. The multiple object position and size determined based on the leaf node points. The leaf node denotes the grid points (*i,j*) and multiple objects depth attains the O(log(n)).

B. Working Principle of Cross out Searching Point

The cross out searching begins with the selection of eight neighbor pixel points on the grid. The eight neighbor pixel point is chosen in the square shape and searching is carried out recursively throughout all the pixels. The cross out searching is performed on the entire image and searching process is carried out faster. The cross out searching is represented in diagrammatic form.

Fig. 4 Cross Out Searching in Remote Sensing Image

The searching process in TGM technique follows the labeled grid form and pixel count represents the location of the square. The square shape is chosen to easily identify the objects in the image. The position *'i'* and *'j'* are the horizontal and vertical position of the grid points. The point at position *(i,j)* is indicates as 1 in TGM technique, then the objects are identified effectively. If, position *(i,j)* is not identified, then the square grid points are moved to the neighboring pixel to identify the particular search result. Likewise, the procedure is continued till the searching result is attained.

After the identification of the objects, it is marked out through the object shape. The points are represented in TGM as,

$$\text{Search objects} = \{i+4, j+4\} \qquad (3)$$

TGM results the best searching of objects till the final iteration and signified with a circle. The working principle is illustrated through steps.

Step 1.Assume the grid point (i,j) in the current frame and set to zero $(i,j)=0$

Step 1.1: Dissimilarity object value in the current grid points is analyzed

Step 2.The correct similarity value of the four neighboring grid points in cross outline is chosen.

Step2.1: Cross outline computed as$((i_1,j_1),(i_1,j_2), (i_2,j_1),(i_2,j_2))$ to attain the exact object

Step 3.If grid point value< 0, then repeat step 2 on the neighboring pixel points

Step 4.Else

Step 4.1: If grid point >0

Identify the object grid point, (i_1,j_1) -upper left or (i_2,j_2) -lower right

Step 4.2:Else

Identify the object grid point, (i_1,j_2) -upper right or (i_2,j_1) -lower left

Step 5.Repeat Step 2 to 4 until all objects are searched

Step 6.Search object in cross pattern depending on the grid point attain O (n) complexity.

The image searching identifies the objects needed with reduced processing time when the labeled grid points used. The previous iteration is used to find the best search results.

C. Matching and Verification Using Gabor Transform Form

In TGM technique, searched objects through the Section II.*B* working steps is now matched with the stored objects to effectively perform the verification step. The verification step performs the subtraction process to detect the object in higher accuracy level. TGM is an efficient technique with background subtraction processing from the image at any given instant of time. TGM subtracts the whole image size with the position and size of the objects to easily remove all unwanted background grid points. The subtraction process is computed as,

$$\textit{Object Detection}=S-(\textit{length}\ (O), (x,r),(y,r)) \qquad (4)$$

'S' denotes the size of the whole image. The image size is subtracted from the object size to easily detect the images.

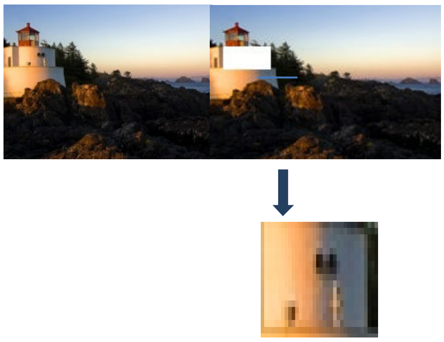

Fig. 5 Background Subtraction Processing

The Gabor wavelet transform in TGM technique consists of solving the complex wavelets and perform the precision recall analysis. In a wavelet neural network, the quad tree based objects determination and cross out searching point is used to easily analyze the time-frequency and detect the objects. Gabor function in TGM technique provides the spectral density which concentrated on a given position and size in a certain direction.

Gabor Function with odd sine function and even cosine function is to easily detect the objects from the remote sensing image in neural network.TGM calculate the sine and cosine derivatives together with a single complex Gabor wavelet transform. For the object detection, the convolution in horizontal and vertical directions (i.e.,) ('i,j')is performed with various wavelets. In TGM, Gabor wavelet based object detection.

$$\text{Gabor Wavelet Object Detection } (i,j,\sigma_{detection}) =$$

$$= \sqrt{O1_{i,j}^{\ 2}(i,j,\sigma_{detection}) + O2_{i,j}(i,j,\sigma_{detection})} \qquad (5)$$

$\sigma_{detection}$ denotes a partial derivative obtained at the position of subtracting the background image. 'O1' and 'O2' are the different types of objects to be detected in the image. *i,j*are the grid points used in the image. The square root of all the objects is computed to attain the Gabor wavelet based object detection in WNN. Gabor wavelet transform based object detection improves the matching result by compare the obtained result with the stored result.

In Tagged Grid Matching, grid similarity function with objects highlights the topological coherence of the match. The grid based similarity function enhances the similarity in the verification process. The grid usage in the object detection reduces the recall ratio in TGM technique. Gabor wavelet transform contains the sine and cosine function to produce the best result on the time-frequency analysis.

III. Tagged Grid Matching Experimental Evaluation

Tagged Grid Matching (TGM) technique is experimented in MATLAB coding. Wilt Data Set is used to easily detect the object which is experimented in MATLAB. The High-resolution Remote Sensing data set contains the large number of land area images and images with normal and diseased trees. Wilt has 4889 instances of multi-variant images and 6 attributes. The wilt dataset consists of image segments, generated after the segmenting of pan sharpened image.

The segments contain spectral information from the Quick bird multispectral image bands and texture information from the panchromatic image band. The testing dataset is for easily detect the diseased tree objects. The ‘w’ in wilt dataset denotes the diseased trees and ‘n’ denotes the land cover. Mean ‘R’’G’ and ‘NIR’ illustrates the red, Green and NIR value of the high resolution remote sensing images. The experiment is conducted on the factors such as multi-object detection rate, object miss rate, processing time, precision factor, and detection accuracy level.

Multi-object Detection demonstrates the detection of the multiples objects with the object determination result. The grid point level is responsible for the effective multi-object detection in the high resolution remote sensing image.

$$\text{Multiobject Detection Rate} = \frac{D_i - D_j}{T_O} \times C_g \qquad (6)$$

where

D_i=*No. of object to be detected*
D_j=*No. of objects detected*
T_o=*Total no. of objects in image*
C_g=*Grid Point Count*

The experiment conducted on Wilt dataset images with ‘100’ objects on the particular image. The object miss rate is defined as the proposition of the system fails to identify the result accurately based on the object determination, searching and verification process. The object miss rate is the inaccurate detection of the objects from the remote sensing images and measured in terms of miss percentage (%).

$$Miss\ Rate = \frac{No.of\ objects\ to\ be\ identified - No.of misses\ objects}{Total\ object\ count} \qquad (7)$$

The total object count taken for experimental evaluation is ‘35’. Processing time is defined as the amount of time taken to complete the object determination, searching and verification process to attain the object detection and measured in terms of seconds (sec). Precision Factor contains all the retrieved objects and evaluated with the rank considering the top most ranking objects. The top most ranking object detection is called precision factor.

$$Precision\ Factor = \frac{Relevant\ Objects\ count \cap Retreived\ Objects\ count}{Retrieved\ Objects} * 100 \qquad (8)$$

Precision Factor measured with the relevant objects and retrieved objects to obtain the best result of accuracy. Detection Accuracy defines the matching of the stored objects and retrieved objects through the TGM technique, which measured in terms of percentage (%).

IV. TGM Result Analysis

In Section IV, Tagged Grid Matching (TGM) technique results are analyzed on the existing Cluster-based algorithm for Co-saliency Object Detection (C-COD) and Super Resolution (SR) scheme. Tagged Grid Matching technique is compared with C-COD and SR scheme through table and graph experimental values.

TABLE I
Tabulation of Multi Object Detection Rate

Grid Point Count in Image	Multi Object Detection Rate (%)		
	C-COD	SR scheme	TGM
250	11	12	13
500	18	20	22
750	28	29	31
1000	40	42	45
1250	46	48	50
1500	57	60	62
1750	65	68	71

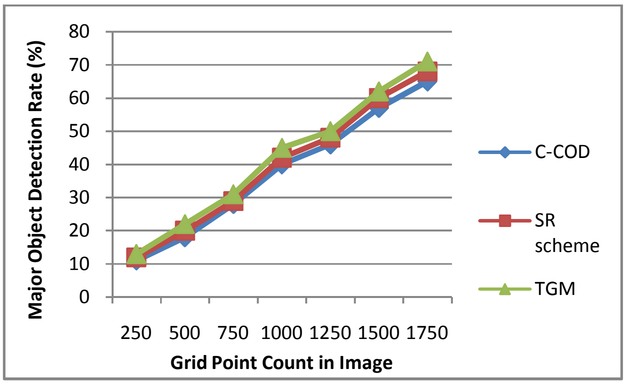

Fig. 6 Performance of Multi Object Detection Rate

Table I and Fig. 6 illustrate the multi-object detection rate based on the grid points in the image. The multi object detected by using the quad tree operation improves the detection rate by 8–22% when compared with the C-COD [1] and 3–10% reduced when compared with the SR scheme [2]. The multiple object position and size determined based on the leaf node points in the quad tree. The leaf node denotes the grid points (i,j) and multiple objects detection depth in the high resolution remote sensing image.

Table II describes the object miss rate based on the object counting the Wilt dataset images. As the object count increases, the miss rate is improved gradually. The miss rate is measured in terms of the miss percentage (miss %).

TABLE II
TABULATION OF OBJECT MISS RATE

No. of objects	Object Miss Rate (Miss %)		
	C-COD	SR scheme	TGM
5	0.13	0.12	0.11
10	0.28	0.25	0.22
15	0.37	0.35	0.31
20	0.51	0.48	0.45
25	0.70	0.67	0.55
30	0.95	0.84	0.72
35	1.12	0.99	0.88

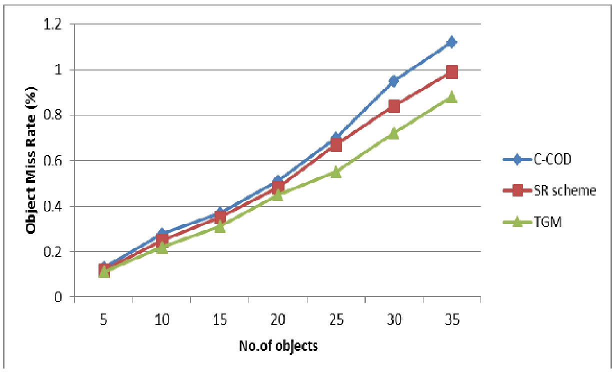

Fig. 7 Measure of Object Miss Rate

Fig. 7 illustrates the object miss rate and TGM technique attains the lesser object miss rate when compared with the C-COD and SR scheme. The Quad tree with objects and four cells on each square form eliminates the object miss rate to larger percentage. In TGM, four cells in Quad treerepresent the equal sized squares by covering all the grid points of the image. The TGM technique 11–24% reduces the object miss rate when compared with the C-COD [1] and 6–17 % reduced when compared with the SR scheme [2].

TABLE III
TABULATION OF PROCESSING TIME

Images	Processing Time (sec)		
	C-COD	SR scheme	TGM
Image_1	322	315	291
Image_2	564	514	465
Image_3	948	815	789
Image_4	1312	1236	1127
Image_5	2189	2080	1928
Image_6	1675	1558	1456
Image_7	2549	2343	2247

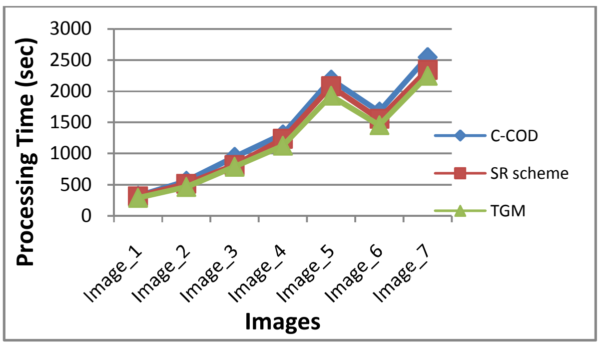

Fig. 8 Measure of Processing Time

Table III and Fig. 8 describe the processing time taken to detect the objects from the high resolution image. The cross out searching point is developed in TGM technique which reduces the processing time by 9–17% when compared with the C-COD [1] and 3-10% reduced when compared with the SR scheme [2]. Cross out searching point carried out the larger area and object detection performs Gabor wavelet transform.

TABLE IV
TABULATION OF PROCESSING TIME

Relevant Objects	Precision Factor (Accurateness value)		
	C-COD	SR scheme	TGM
5	115	121	125
10	102	105	111
15	96	101	107
20	100	110	115
25	103	112	118
30	104	111	119
35	103	113	120

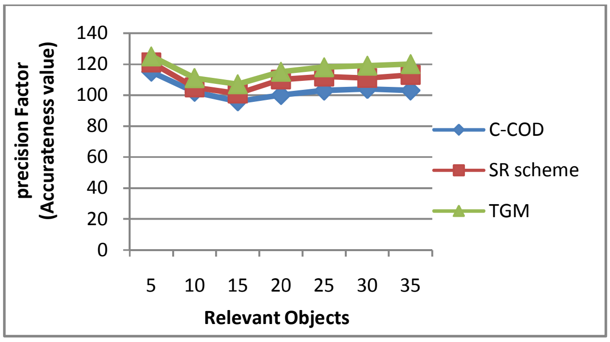

Fig. 9 Precision Factor Measure

Fig. 9demonstrates the precision factor of the C-COD, SR Scheme and TGM technique. Table IV shows the processing time for the existing and proposed system. The Gabor wavelet transforms in TGM technique solving the complex wavelets and attains the higher precision results. In TGM technique, the quad tree based objects determination and cross out searching point is used to easily analyze the frequency of wavelets and detect object with higher precision factor. The precision factor is gained by 8–16% when compared with C-COD [1] and 3-7% improved when compared with SR scheme [2]. TGM subtracts the whole image size with the position and size of the objects to easily remove all unwanted background grid points and attain higher precision factor.

TABLE V
TABULATION FOR DETECTION ACCURACY LEVEL

No. of Images	Detection Accuracy Level (%)		
	C-COD	SR scheme	TGM
8	83	77	87
16	70	69	75
24	74	72	77
32	67	66	72
40	80	75	84
48	88	84	93
56	88	83	92

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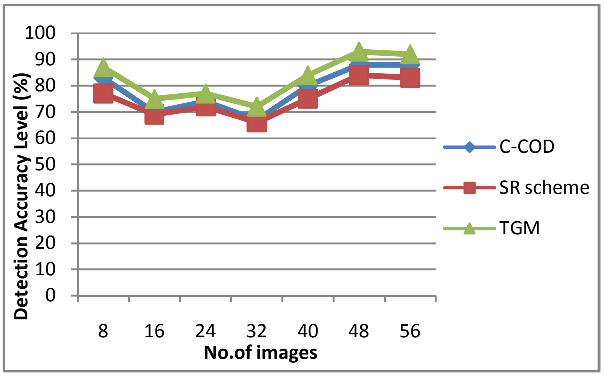

Fig. 10 Detection Accuracy Level Measure

The detection Accuracy level is measured and demonstrated in with values in Fig. 10 and Table V. Gabor function in TGM technique provides the spectral density on a given position and size in a certain direction to improve the accuracy level of object detection. The Gabor wavelet transform is performed to improve the matching and attain the accuracy level while detecting the objects in TGM. Object detection accuracy is 4–7% improved when compared with C-COD [1] and 6–12% improved detection in TGM when compared with the SR scheme [2].

Finally, TGM technique works determines the object position and size. The cross outlines checks the eight neighboring grid points and achieves the faster searching process with lesser miss rate. TGM is an efficient technique for object detection, where the background subtraction processing take place on the high resolution remote sensing image.

V. Related Work

Existing Super Resolution (SR) scheme for landmark images identifies the related regions in [2] and diminish the mismatching rate. Structure-aware matching criterion and adaptive block sizes attain the plotting accurateness among low and high resolution piece of image. But the Structure-aware matching criterion is not paying attention to detect multiple regions in SR images and fail to enhance the result percentage of object detection.

A corner based approach as demonstrated in [8] identify text and caption from videos. Corner based approach exists dense and logically presence of corner points in characters, especially in text and caption. The corner points easy to implement and easily applied to extract in video programs with diverse languages. Pre-trained boosting-style detector encodes a priori information in the form of selected features and weak classifier weighting in [10] which maximally utilizes the correlated training data. CovBoost does not have the ability of online learning to handle the time-varying scenes.

Boosted Greedy Sparse Linear Discriminant Analysis (BGSLDA) as presented in [3] capably teaches a detection cascade. BGSLDA develop the sample reweighting property of boosting and the class reparability criterion but fails to focus on the more efficient weak classifiers and online updating learned model. Gaussian-distributed measurement matrix as established in [4] constructs an object appearance model. The model detects by semi-supervised learning process but feature selection is not combined with any representation of a feature space in future.

A supervised learning algorithm as illustrated in [11], [19] switch visual drift successfully and resourcefully in MIL tracker. An online discriminative feature selection algorithm which optimizes the objective functions in the steepest ascent track with reverence to the optimistic samples to the negative ones. A feature selection approach dynamically chooses additional practical features than MIL tracker by using the Fisher information measure. The criterion measures the uncertainty of classification model.

The synthetic and clinical phase contrast magnetic resonance angiographic volumes as illustrated in [15], is more computationally proficient than the conservative spatial implementation. Content Based Image Retrieval (CBIR) provides the composite configuration in [20] where the ranking features are extracted from each region and block. Pair wise and List wise learning concept are used to rank the suitable CBIR application.

VI. Conclusion

Tagged Grid Matching presented the work with the three components to detect the objects from the high resolution remote sensing image. TGM technique performs the matching process by using the three components. The position and size of objects in the current image is determined using the Quad tree based object determination. The Quad Tree denotes the node as objects and determines the position and size using the hierarchical grid points. TGM performs the object searching using the cross out searching point and averagely reduces 7.273% processing time, as compared with the SR scheme. Subtract operation take place to remove the background image from the high resolution image for fetching the accurate objects. The Gabor wavelet transform used to improve the object detection accuracy level. Labeled Grid employs effective interactions in the grid and provides the result to achieve significantly better object detection results from the high resolution remote sensing images. Experimental result provides the significant improvement on the multi-object detection rate, and precision factor.

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