Multi-class vehicle type's recognition system using spatial visual words with minimized feature set

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ABSTRACT

Visual vehicle detection and recognition are very important issues in road development study. It gives insightful statistics for the purpose of building-up road infrastructure, road maintenance and future development of road capacity. It is very important to keep stability of road traffic and safety with comfortable travel. In the literature, many approaches have been introduced to improve the multi class vehicle recognition. Through computer vision techniques, the paper introduces a method that uses the correlation among patches to measure the similarity between images. According to this approach, a set of HOG and SURF local features is extracted from a given automobile image. Then, the distance between these local features is computed against the visual codebook, which was previously constructed by K-means. The analysis applied to the Naively combined features result in getting better computational performance in recognition. KNN, and SVM, were used for data analysis and the results indicate that the proposed method gives promising results on the UIUC car detection dataset. Moreover, a combinatorial gray wolf optimization method was employed to determine the best recognition with less local feature set.

Keywords: Vehicles recognition, Local feature extraction, SURF, RBF, SVM.

1. INTRODUCTION

Visual Multi-class vehicle recognition is exceptionally basic issues in various applications of computer vision. The vehicle type recognition execution relies upon how informative and discriminative components are utilized to depict the substance of visual vehicle type. In the literature, the most utilized local descriptor calculations that depict image utilizing and accumulation of local feature vectors are SIFT [1] and SURF [2]. These descriptors are widely utilized as a part of perceiving visual Multi-class vehicle type. One downside can be found in utilizing these local descriptors, as a part of an image, is that it gives substantial component representations. These components are too intricate to be handled by machine learning algorithms. Therefore, the bag of visual keyword representation has been proposed [3].

In the bag-of-word approach, the most commonly used machine learning algorithm for clustering is K-means. One of the important attributes in clustering is the number of clusters or K's used to describe a Multi-class of vehicles. This variable is unknown and needs to be optimized to produce better results. The principle of this work is to abuse the description of a spatial substance of visual words in the Multi-class of vehicles. It is used to screen the impact of these vehicles on the road for the purpose of studying road maintenance.

The great execution of characterization for the BOW has driven researchers to consider building more connections between various visual keywords for enhancement purposes [4, 5, 6, 7]. The histogram of the less composed request of visual catchphrase is known as the hard back of-features (HBOF) [3]. At the point, when every feature in the image is utilized for representing winning group centroids (or a catchphrase in the visual codebook), the other bunch centroids are ignored for the description. To enhance the HBOF, various novel strategies in back of visual keywords have been proposed, as in [8], [9] and [10]. These strategies include utilizing a "soft assignment" which mulls over all bunch of centroids for the description as an enhanced way for depicting objects. In this paper, Gray wolf optimization method was utilized to enhance feature set selection for vehicle image recognition.

This paper is organized as follows. Section 2 review some of the works on vehicles recognition and other related works with the used algorithms. Section 3 through 5 describes the requirements and parts of the vision systems for vehicle recognition. Section 6 describe feature selection minimization using Binary Gray Wolf Optimization. Section 7 lists the results obtained from the proposed methodologies. Finally, section 7 gives an overall conclusion driven from this work.

2. RELATED WORKS

One of the principle issues, in the visual multi-class of vehicles recognition systems, originates from the obscure inquiry image outcomes from the search purpose as in [11, 12, 13]. The recognition outcome turns out to be more terrible as the images are disturbed by transformations such as translation, rotation, scaling and disturbances due to variations. Therefore, to enhance the productivity of developments in our surroundings (particularly in vehicle transportation), it is important to introduce a modern recognition of vehicles. This recognition ought to be supported with intelligent techniques or Computer vision strategies to accomplish the reason for this paper. At the end, numerous algorithms have been proposed and used to separate the local features of those vehicle images. The quality of local features fundamentally relies on the substance or structure of images.

The local features are discriminative, meaning, rotation or partial illumination can change the image content. Also, it is important to define the relationship of these features such as their spatial relationships within the image scene [14, 15, 16]. This relationship approach involves clustering features like SURF by using K-means clustering algorithm on the bag of visual keywords. This approach has shown a good performance in image scene recognition applications [17]. The K-means clustering algorithm is commonly used for clustering features in approaches which are similar to bag of visual keyword [18]. Some of the previous works incorporated the use of weights for each cluster centroid [9, 10]. The performance of the combined features has resulted in faster computations of combined features used with integral images [19, 20]. Moreover, covariance features have been introduced by Wangy and Yangz for Haar-Like features that are used for computing descriptors for the region represented by the integral image, so the dimensionality is much smaller. In all the listed works the combined is implemented on the raw pixels like intensity, color gradients, etc. [21]. Finally, the covariance was also used with SVM for classification in different approach called Locality-constrained Linear Coding [22]. In General, the combined implementation results of the previous studies indicate promising results for recognition process.

3. METHODOLOGY

In this section, the proposed system methodology is discussed. The system consists of feature extraction which includes SURF and HOG. Next, the feature set is minimized using binary Gray Wolf Optimization for best recognition results. Finally, the classification is explained for combined feature set.

3.1 SURF FEATURES

Speeded Up Robust Features known as SURF is a vigorous image identifier and descriptor, introduced by Herbert Bay et al. [2]. It could be used as a part of computer vision errands like vehicle recognition or 3D reconstruction. The standard version of SURF used for feature extracting is faster than SIFT, since it is based on integral of images. Hessian Matrix is one of the tools used in SURF algorithm to extract image features. The following subsections illustrate the calculation of interest point extraction and repeatable angle calculation.

3.1.1 INTEREST POINT EXTRACTION

In this stride, the algorithm begins with calculating the Hessian matrix's determinant and extracting local maxima. The Hessian matrix calculation is approximated with a mix of Haar basis filters in progressively bigger levels. Hence, for an image of size m×n the complexity will be (mnlog2(max(m,n))). At every scale, interest points are found to be those points that are local extrema of both the determinant and trace of the Hessian Matrix at the same time. At any location x y, and scale σ the Hessian Matrix is characterized as [2].

$$H(x,y,\sigma) = \begin{bmatrix} L_{xx}(x,y,\sigma) & L_{xy}(x,y,\sigma) \\ L_{yx}(x,y,\sigma) & L_{yy}(x,y,\sigma) \end{bmatrix} \tag{1}$$

Where Lxx(x,y, σ) is the convolution of the derivative of Gaussian second order with the image I at pixel x, y. The outcome of this step will represents a set of interest points with their scales as in key points localization in SURF algorithm.

3.1.2 REPEATABLE ANGLE COMPUTATION

A repeatable edge is extracted for every interest point before registering the feature descriptor. This stride registers the angle of the gradient encompassing the interest point, then the maximum angular reaction is picked as the direction of the feature.

In this work the SURF features clustered then naively combined with the Histogram of the Gradient (HOG) to form more invariant features for recognizing multi class vehicles. The idea is that the combination of multi features related to the same image can give more robust feature that can be more reliable for these applications.

3.2 HISTOGRAM OF ORIENTED GRADIENT (HOG)

HOG algorithm divides the original image into sub image windows or sub spatial regions. Then, for every region, a local histogram of gradient directions will be gathered. The mix of these histograms for every region will outline the representation of the entire image. This will construct better features invariance regardless of image illumination, shadow, and so on. These histograms can be normalized and utilized with their measurements to differentiate the local reactions. This prompts bigger spatial region which can be utilized for normalized descriptors such as Histogram of Oriented Gradient (HOG). The method has been utilized by [13, 4, 5] as a part of expansion to SIFT approach. The promising results and accomplishment of these descriptors drove researchers to utilize them and combine them naively with SURF features for Car or vehicle recognition.

3.3 CLASSIFICATION

The recognition process in this work is essentially used by Naively combining HOG of the vehicle image scene with minimum distance (MDT) of vehicle image codebook (B). The codebook was built previously from the dataset of various vehicle images. The measure of MDT, is a vector of specific size. The covariance matrix of the applicable part of the scene image will be calculated. This will help to figure out the correlation between every two combined vectors in a highly accurate rate. Finding the significant part for MDT is possible by computing the Euclidean's distance between the middle of image MDT and all other sorted minimum distance that situated in all datasets. The smallest contrast worth will be chosen in order to exchange it with MDT, then afterward the covariance will be taken. Figure1. demonstrates the fundamental steps utilized as a part of preparing the query image.

Optimization of cluster (K) for the codebook (B) is a basic procedure, since the covering and over fitting for the quantized feature prompts issues; in this way optimization for K is required. The covariance of minimum distance varying for all the codebook can be effectively segregated from other distance distributions for other feature vectors. To inspect the likeness of two images like x and y, the covariance for x and y must be ascertained. The relationship between the two combined feature vectors x and y is essentially expressed as:

$$corr(cf1, cf2) = \frac{cov(cf1, cf2)}{std(cf1) * std(cf2)} \tag{2}$$

Where, the correlation coefficient is Pearson's coefficient for the two variables cf1 and cf2, varies between -1 and +1. The work was developed in Matlab framework where cov(x,y) computes the combined matrix of x and y.

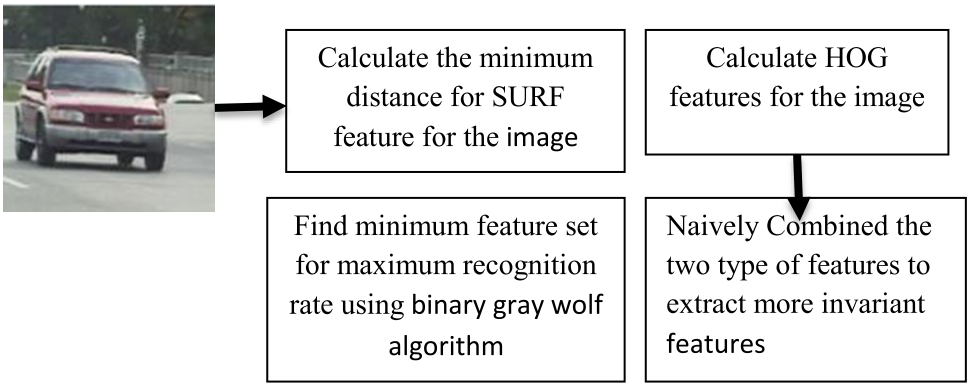

FIGURE 1. Calculating combined features for image

In general, the acquired results for all correlation values are sorted; then, the maximum values are taken to be the best matching visual vehicle. This approach is also called as a k nearest neighbor (k-NN). The combined approach gives good information about the scene spatial domain. Additionally, the correlation of the combined matrices built on constructed distance tables for the feature vectors that provide more accurate measures in support of certainty of recognition, through spatial domain matching.

Each section should have a heading. All headings (except for the headings for the abstract, keywords, acknowledgements, list of symbols (if any) and references), should be numbered using the Arabic numbering system. All headings should be in Times New Roman font, point size 12, and flushed to the left. Leave a spacing of one character between the number and the title of the heading.

3.4 FEATURE SELECTION USING BINARY GRAY WOLF OPTIMIZATION

Feature selection optimization is mainly used to determine the effect of different features on the recognition step. This technique is used to find the minimum feature subset of the feature space which increases the difference between the target classes [23]. In this research, Binary Gray Wolf optimization (BGW) is used for minimizing the feature subset of SURF, HOG and Combined MDT_SURF-HOG. It will give an insight about the effect of each subset on the final recognition step, as well as, reducing the number of extracted features from each sample. The later can prove very crucial in case of real time recognition when the processing time should be minimal
Gray Wolf optimization algorithm is based on the gray wolf pack social relationship and hunting behavior [24, 25]. For mathematically modelling GWO, the fittest solution is called the alpha (α), the second and third best solutions are called beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω). The hunting is guided by α, β, and δ, while ω follows these three candidates.
The encircling behavior during hunting can be modelled as a directional vector of the prey position XP(t) and gray wolf position X(t+1) as,

$$\vec{X}(t+1) = \vec{X}_p(t) + \vec{A}.\vec{D} \tag{3}$$

Where A is coefficient vector and D is found from,

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \tag{4}$$

The A and C coefficient can be calculated from,

$$A = 2a.\vec{r} - a \tag{5}$$

$$C = 2\vec{r}_2 \tag{6}$$

Where a is decreased from 2 to 0 over the course of iteration and r1 and r2 are randomly generated values in the range of [0, 1].

In order to mathematically create the hunting behavior of grey wolves, the alpha (best candidate solution) beta (the second best candidate solution), and delta (the third best candidate solution) are assumed to have better knowledge about the potential location of prey. The first three best candidate solutions obtained during each iteration and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. So, the updating for the wolves positions is as

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{7}$$

Where the vectors X1, X2 and X3 is calculated using the following,

$$\vec{X}_1 = \left|\vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha\right|$$
$$\vec{X}_2 = \left|\vec{X}_\beta - \vec{A}_2.\vec{D}_\beta\right|$$
$$\vec{X}_3 = \left|\vec{X}_\delta - \vec{A}_3.\vec{D}_\delta\right| \tag{8}$$

Here Xα , Xβ and Xδ are the first three best solutions in the pack at iteration t. A1, A2 and A3 is calculated using Eq. (5) and Dα , Dβ and Dδ is calculated using Eq. (4). Equations (7) and (8) are basically used for continuous optimization problems, however, the feature selection problem involves very limited binary scale (0 for not selected feature and 1 for selected feature) model. Therefore, binary Gray Wolf optimization algorithm based on [23] is used to replace Eq. (7) above by the equation,

$$X_d^{t+1} = \begin{cases} 1 & if(sigmoid(\frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}) \geq rand \\ 0 & otherwise \end{cases} \tag{9}$$

With,

$$sigmoid(a) = \frac{1}{1 + e^{-10(x-0.5)}} \tag{10}$$

X_d^{t+1} is the bit at position d in the solution which is find by the corresponding bit in X1, X2 and X3.

4. EXPERIMENT AND RESULTS

4.1 VEHICLE DATASET

The experiment was conducted using the dataset of UIUC [24]. SURF algorithm was used to extract features. All the experiments were done by a laptop computer with these specifications: speed 2.6 GHz core i5 and 4GB memory.

K-means algorithm has been used to construct feature vectors, with a set of different cluster numbers of 260, 275, 350, 400, 450, 500,520,600,650 were employed. To classify or recognize the vehicle, the best K was used to classify the features for the tested images for different groups of vehicles namely a station, salon, truck, pickup under various situations related to these vehicles. The feature vectors of SURF gave an average of 250 features per image. This indicated the total features for all images in the data. For an M features of SURF, for any image in the dataset, would give M by K values which resulted from calculating the distance of the tested features against the centroid of the codebook.

For the feature selection result using BGW, the 175 features of BOW and 80 features of HOG were tested for best recognition rate and minimum feature subset. These two was later tested against the obtained minimum feature subset of the combined 250 feature set. Table 1 illustrate the obtained results for the minimum subset against the recognition rate using 66% for training and 34% for testing.

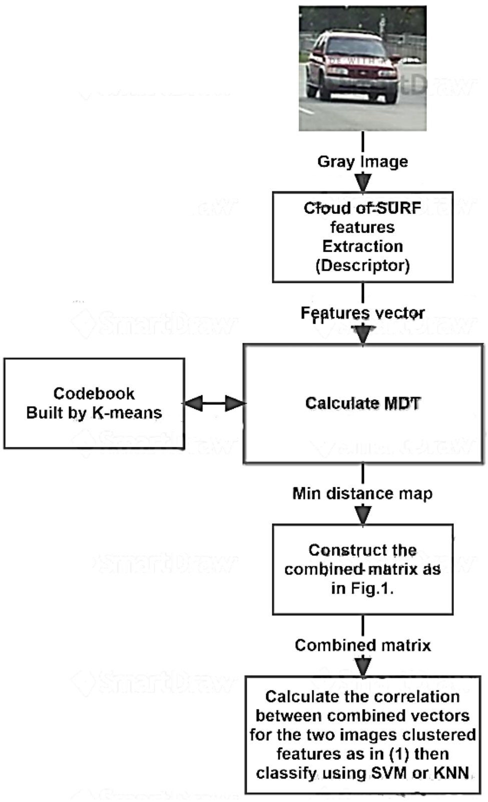

FIGURE 2. The system architecture

As it can be noted from the optimization result in table 2, the combined subset has used only 23 features from the 250 total features. This is very interesting as the separated features has scored only 46 and 26 from the 175 and 80 features of BOW and HOG respectively

This shows that it is not necessary that the combined features subset will depend on the separated minimum subset when tested for recognitions. Moreover, it is also important to note that the set of features used for the combined method are marginally different from that used in the separated BOW and HOG sets as shown in Table 2.

TABLE 1.
Minimum Feature subset for BOW, HOG, MDT and Combined Features

Set	No. of Features	No. of Minimum Features Subset
BOW	175	46
HOG	80	26
MDT	70	36
Combined	250	23

TABLE 2.
Minimum features subset indexes.

Methods	Feature Number
BOW	9,10,11,19,23,24,25,29,32,36,41,49,50,52,53,58,59,61,64,65,66,78,83,90,91,97,102,105,107,110,114,117,119,128,132,143,144,146,149,150,157,159,160,165,168,169
HOG	12,15,25,28,32,33,34,37,38,41,42,43,46,47,49,50,52,53,55,61,63,69,73,75,77,79
Combined	18,19,28,30,36,40,41,44,47,90,102,107,109,118,127,134,178(3),190(15),205(30),216(41),235(60),237(62),249(64)
Similarity with BOW	19,36,41,90,102,107
Similarity with HOG	15,41

From Table 2, it can be noted that the common features with the original feature subset used for recognition with BOW and HOG have less than 15% contribution in the final combined set. Moreover, the contribution of the BOW and HOG in the final feature set has a ratio of 16 out of 175 features and 7 out of 80 features respectively. That means, BOW has 9.14 % of the total features selected in the combined subset compared to 26.28% of features when BOW feature used for recognition, while HOG has 8.75% of the total features selected compared to 32.5% when HOG feature used for recognition. In overall, this shows that features used for separated BOW and HOG recognition are not necessarily the same in the combined feature subset, or neither the final set will be from the separated feature subset. Figure 3 shows the chart for feature minimization process.

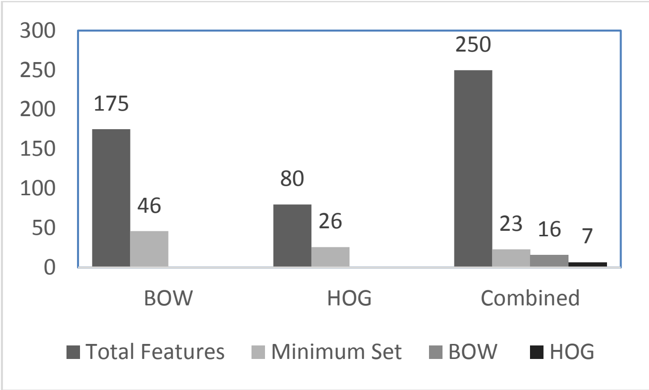

FIGURE 3. Feature subset minimization result for BOW, HOG and Combined features.

4.2 EXPERIMENTAL SETUP

The experiment implemented using SURF grid algorithm. The feature vectors were quantized using K-means clustering. For evaluating the proposed approaches, the whole images in UIUC were divided into two groups. Different running tests were used 5 times. Then, the performances for the two datasets were reported using the average of the obtained classification results.

4.3 RESULTS ON VEHICLE RECOGNITION

Visual vehicle recognition was implemented in this work. To put on view the performance of the system, the algorithm was implemented for recognizing different classes of vehicles including station, salon, truck, pickup. The Comparison with the other approaches is illustrated in Table 3 using UIUC dataset. The table correspond to vehicles groups; and these groups was increased to demonstrate the accuracy of the approach.

TABLE 3.
Recognition Rate for BOW, HOG ,MDT and Combined Features

Set	No. of Minimum Features Subset	Recognition Rate
BOW	46	50.8671 %
HOG	26	64.1618 %
MDT	36	76.5412 %
Combined	23	82.2857 %

From the obtained results on UIUC dataset, it is obvious that the combined features approach gave a better result than the others including BOW. This is because the grid SURF is more informative features than standard for the image scene to construct the cloud of the features. Moreover, the use of GWO for the feature minimization led to a set of combined feature vector for the spatial information of cluster distances. One issue to achieve better vehicle recognition is that, the way of optimizing the cluster number (K) to build the codebook. For that sake, a trial and error process was implemented in this work. The best result of BOW approach indicates that K was the best optimized cluster used to build the codebook. The error obtained in vehicle recognition was because of the K value selection. The criterion for vehicle's image scene recognition is resolute by the majority of retrieved image related to each group. In the correlation values ranging between +1 and -1, the value closest to +1 denotes more similarity to the query image (Q) as in Eq(1). It should be noted that the qualities of the used images are low but a good rate of correct recognition was scored.

5. CONCLUSION

The correlation of combined vectors is a reasonable approach for visual vehicle recognition in comparison with the others. The experimental results showed that spatial combined of minimum distance, using clustering SURF features to recognize the visual object and vehicle, significantly outperforms other approaches. The approach can be used with other features extraction algorithms to increase the speed of recognition. The results also showed that the combined approach mainly depends on the clustering features and optimizing them to get the best K for the best result of recognition. It is an establishment of an algorithm to conceptualize the surroundings using spatial clouds of features with SURF techniques. The successful use of this approach can lead to better vehicle recognition and as a result a better application related to road traffic and maintenance.

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RESOLUTION AND INFLUENCE OFDXX-824-960/1710-2170-65/65-17I/17.5I-M/M-C IN MOBILE PHONE BASE STATIONS IN RANYIA CITY

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ABSTRACT

The aim of this paper is to evaluate the solution and influence of antenna type Dxx-824-960/1710-2170-65/65-17i/17.5i-M/M-C In Mobile Phone Base Stations in Ranyia City. Huawei Agisson undertakes to enhance customer success by rapidly responding to customer demands and providing customers with profitable and sustainable base station antenna products and solutions through innovative technologies and outstanding operation by compared with Kathrin type of antenna. the reason for choosing this type is because it have very good properties from the other types . In Raniy a city there are 24 site three sectors and just two sites in 2 sectors. One site have the type Telos for HSN 47 Hz. Almost of the sites include the type K742225 near to 15 sites have this type of antenna. And two other sites have the antenna type [DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C]. In this paper a Simulation results indicate that Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C depends on the network environment and different environments may lead to different optimization results in terms of capacity and coverage performance.

Keywords: DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C Antenna, Huawei Agisson Kathrin antenna, K742225, capacity, Coverage.

1. INTRODUCTION

Cellular Networks achieve large capacity capabilities by reusing given frequencies repeatedly in a given system. This concept means that the communication paths are interference limited as opposed to traditional radio systems that were noise limited. To minimize interference, the use of sectorized antennas have been employed, each of which provides coverage to a portion of the cell. In a three-sector arrangement, each sector antenna covers a 120-degree pie shape that extends some distance away from the antenna site. Ideally, each sector antenna should only provide coverage in its 120-degree pie shaped sector so that interference with adjacent sectors is minimized [1].

By holding the consistent concept of customer orientation in mind, Huawei Agisson undertakes to enhance customer success by rapidly responding to customer demands and providing customers with profitable and sustainable base station antenna products and solutions through innovative technologies and outstanding operation [2].

In 2004 based on a deep understanding of wireless communication systems as well as the application experience in antenna, Huawei Agisson start the base station antenna self-development. Through years of efforts, Huawei Agisson has developed single-band, dual-band, and multi-band antenna series to meet the GSM / UMTS / CDMA / and TDSCDMA/ LTE /WiMAX and other system needs. Through strict testing and authentication, Huawei Agisson products have been gradually deployed by famous carriers in China and abroad, including Vodafone, STC, Telefonica, MTN, BSNL, ET, Zain, China Unicom, China Telecom, etc. At present, Huawei Agisson antennas have been deployed across the world and serve over 200 carriers in more than 90 countries Fig. (2) Show the Addition of new carriers of Huawei Agisson antenna / year [2].

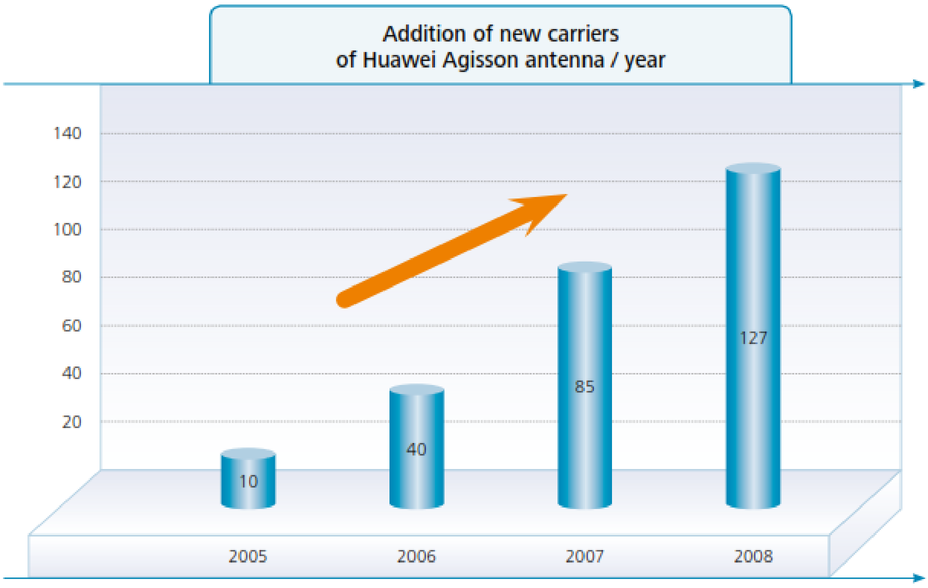

FIGURE 2 .The Addition of New Carriers of Huawei Agisson Antenna / Year

Multiple antennas at the base stations may be used to form multiple beams to cover the whole cell site.Three beams each with a 120^0 beam width (or six beams each with 60^0 beam width) can be used for this purpose. The coverage of each beam is then treated as a separate cell. Traditional base station installations of mobile communication make use of space diversify techniques, which require at least two antennas pointing in the same direction and separated by a distance of 10 to 20 wavelengths [10].

2. THEORY

2.1 ELECTRICAL PROPERTIES

The electrical properties for the Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C is shown in fig. (3) [2].

Electrical Properties																
Frequency range (MHz)		824 -894			880 -960			1710-1880			1850-1990			1920-2170		
Polarization		±45°														
VSWR		≤1.5														
Gain (dBi)	(°)	0	4	8	0	4	8	0	4	8	0	4	8	0	4	8
	(dB)	16.7	16.8	16.5	17.1	17.2	16.9	16.7	16.9	16.6	17.0	17.2	16.9	17.3	17.5	17.2
Side lobe suppression for first side lobe above horizon (dB)	(°)	0	4	8	0	4	8	0	4	8	0	4	8	0	4	8
	(dB)	18	17	16	18	17	16	18	17	16	18	17	16	18	17	16
3dB beamwidth (horizontal)		67°			65°			67°			65°			63°		
3dB beamwidth (vertical)		8.3°			7.2°			8.0°			7.5°			7.0°		
Isolation between portsw (dB)		≥30														
Front to back ratio (dB)		≥28						≥25								
Cross polar ratio(dB)	0°	≥18														
	±60°	≥10														
Electrical downtilt		0° - 8°						0° - 8°								
Intermodulation IM3 (dBc)		≤-150 (2 x 43 dBm carrier)														
Max. CW input power (W)		300						200								
Max. power per combined input (W)		500														
Impedance (Ω)		50														
Grounding		DC ground														

FIGURE 3. The Electrical Properties

From fig (4) the frequency range for the Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C is 824-960 for polarization ±45°where the gain (dBi) between 16.7- 17.2 and electrical down tilt is 0° - 8°with VSWR ≤1.5and Max. power per combined input (W) is 500 and for frequency range 1710-2170 for same polarization while the gain (dBi) between 16.7- 17.5 and same electrical down tilt with same VSWR and Max .Polarization is defined as ' the orientation of electric field of an electromagnetic wave '. In other words, it is the direction of the electric field. Polarization is in general described by an ellipse. The ratio of the maximum to minimum linearly polarized responses on the ellipse is the axial ratio [5].
Gain is a measure of the ability of the antenna to direct the input power into radiation in a particular direction and is measured at the peak radiation intensity, or is measure of directivity properties and the efficiency of the antenna.
The relationship between gain and directivity is given as [5], [9]:

$$\text{Gain} = \text{efficiency X directivity} \qquad (1)$$

For Kathrein there is no difference only the beam that point to the sky that become bigger. Also in horizontal plane the back lobe of Huawei antenna is bigger [3] .power per combined input (W), as Shown in fig (3). [2].

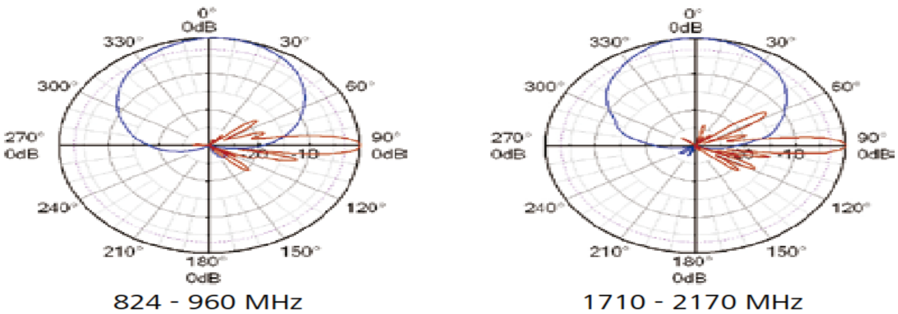

FIGURE 4 .The frequency range for the Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C

Huawei have bigger vertical beam width than Kathrein however the gain of1800 band of Huawei is smaller. But back lobe of Huawei antenna is quite big for this pattern [3, 7].

2.2 MECHANICAL PROPERTIES

Until recently, the accepted method for Mechanical properties for the Huawei. Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C was to mechanically alter its position on the tower. As shown in Fig (5). Where the Dimensions (H × W × D) (mm) is 2449 × 368 × 99 and Net weight (kg) is 26.7 and the Mechanical downtilt are between 0° - 15° at Operating temperature (°C) range between - 55 - + 65 at last Max. Wind velocity (km/h) is 200. The antenna represents a fixed unit capable of tilting along one plane only. As the front tilts down to lower the gain on the horizon, the back tilts up, changing the frontto-back ratio and increasing inter-sector interference [9].Utilization of antenna mechanical down tilt has been a tool for radio network planners to optimize networks .It has been observed to be an efficient method to reduce other-cell interference in the main-lobe direction [6], [9].

Mechanical Properties	
Dimensions (H × W × D) (mm)	2449 × 368 × 99
Packing dimensions (H × W × D) (mm)	2756 × 498 × 220
Net weight (kg)	26.7
Bracket weight (kg)	7.8
Packing weight (kg)	41.6
Mechanical downtilt	0° - 15°
Mast diameter (mm)	50 - 115
Radome material	Fiberglass
Operating temperature (°C)	- 55 - + 65
Windload frontal (N) Windload lateral (N) Windload rearside (N)	1152 (v=150km/h) 270 (v=150km/h) 1152 (v=150km/h)
Max. wind velocity (km/h)	200
Connector	2×7/16 DIN Female

FIGRUE 5. Mechanical Properities

When mechanically and electrically down tilted antenna patterns are compared side by side, the ability of the electrically down tilted antenna to reduce anomalies such as pattern blooming becomes apparent[9]. The use of electrically down tilted antennas has increased significantly since the technology was first introduced. RF engineers, however, continue to apply the same basic guidelines initially developed to help compensate for the limitations of mechanical down tilt antennas. Additionally, many operators have begun to use mechanical down tilt in tandem with electrical down tilt. While combining the two methods can be effective in very limited applications, data suggests that overall this practice leads to horizontal pattern deformations that can all together offset the benefits of electrical down tilt fig.3 shows the Electrical vs. mechanical down tilt angle comparison [8]. As shown from fig (6) a simple explanation for the name of the Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C [2].

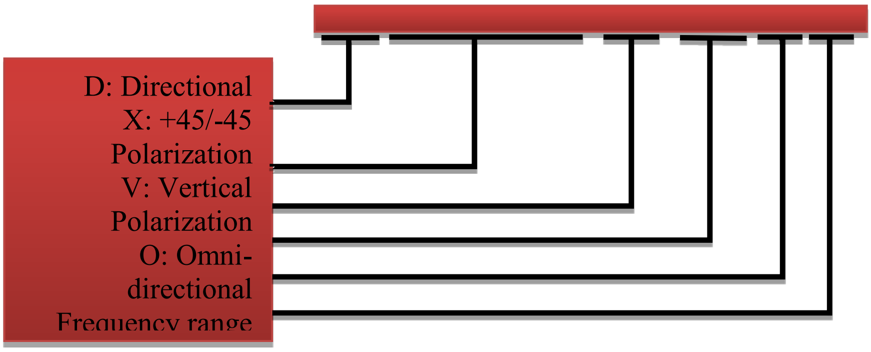

FIGURE 6. Simple explanation for the name of the Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C

The best type for Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C. The Easy RET antenna solution can effectively resolve these problems. This solution facilitates installation, maintenance, and usage of the RET antenna; therefore, the O&M efficiency is improved. The solution has the following features [4].

Free of configuration, Free of calibration, Free of RCU installation, Free of manual recording of bar codes, High reliability, Excellent performance.

3. SIMULATION RESULTS

From table (1) show the antenna type that used in Raniya city in Kurdistan Iraq. There are most type used in this city is almost kathrin type of antenna and the other is for the Huawei Agisson antenna type DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C. The reason by choosing this type is because it have very good properties from the other types Kathrin antenna types. Statistic shows no problem after change antennas to Huawei for the existing sites and some sites have better performance after change the antenna. However we suspect the antenna problem or other factors because only one site has this effect.

As shown in raniya city there are 24 site three sectors and just two site in 2 sectors. One site have the type Telos for HSN 47 Hz. Almost of the sites include the type K742225 near to 15 sites have this type Antenna. And two other sites have the antenna type [DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C]. Just to know there is one site in raniya holding antenna type Telos this site is skarta_0619. And the other sites have different antenna type like K739684, K739686, K730378 and K739623. That clear from the chosen sites are the antenna type K742225 are favorite for Asia cell because it is has very good capacity also for the gain and the beam width. So it have good performance.

TABLE 1.
The Antenna Type That Used In Raniya City in Kurdistan Iraq

Antenna type	SITE	Antenna type	SITE
K742225	Bitwen_0738	K742225	Raniyah_0620
K742225	Bitwen_0738	K742225	Raniyah_0620
K742225	Bitwen_0738	K742225	Raniyah_0620
K742225	Chwarqrna2_0737	K742225	Raniyah1_0670
K742225	Chwarqrna2_0737	K742225	Raniyah1_0670
K742225	Chwarqrna2_0737	K742225	Raniyah1_0670
DXX-824-960/1710-2170-65/65-17i/17.5iM/MC	Chwarqurna_0621	K742225	Raniyah2_0644
DXX-824-960/1710-2170-65/65-17i/17.5iM/MC	Chwarqurna_0621	K742225	Raniyah2_0644
DXX-824-960/1710-2170-65/65-17i/17.5iM/MC	Chwarqurna_0621	K742225	Raniyah2_0644
K742225	Raniyah_0620	K742225	Raniyah3_0643
K742225	Raniyah_0620	K742225	Raniyah3_0643
K742225	Raniyah_0620	K742225	Raniyah3_0643
K742225	Raniyah1_0670	K739686	Raniyah4_0732
K742225	Raniyah1_0670	K739686	Raniyah4_0732
K742225	Raniyah1_0670	K739686	Raniyah4_0732
K742225	Raniyah2_0644	K739686	Raniyah5_0677
K742225	Raniyah2_0644	K739686	Raniyah5_0677
K742225	Raniyah2_0644	K739686	Raniyah5_0677
K742225	Raniyah3_0643	K742225	Raniyah6_0686
K742225	Raniyah3_0643	K742225	Raniyah6_0686
K742225	Raniyah3_0643	K742225	Raniyah6_0686
K742225	Raniyah6_0686	K739684	Sangasar_0747
K742225	Raniyah6_0686	K739684	Sangasar_0747
K742225	Raniyah6_0686	K739684	Sangasar_0747
K742225	Skarta_0619	Telos	Skarta_0619
K742225	Skarta_0619	Telos	Skarta_0619
K742225	Skarta_0619	Telos	Skarta_0619
K739684	Tawela_0679	K730378	Halsho_0678
K739684	Tawela_0679	K730378	Halsho_0678
K742225	Bitwen_0738	K739623	Khandaka_0685
K742225	Bitwen_0738	K739623	Khandaka_0685
K742225	Bitwen_0738	K739623	Khandaka_0685
K742225	Chwarqrna2_0737	K730378	Makok_0714
K742225	Chwarqrna2_0737	K730378	Makok_0714
K742225	Chwarqrna2_0737	K730378	Makok_0714
DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C	Chwarqurna_0621	K739684	Chwarqurna3_0710

DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C	Chwarqurna_0621	K739684	Chwarqurna3_0710
DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C	Chwarqurna_0621	K739684	Chwarqurna3_0710

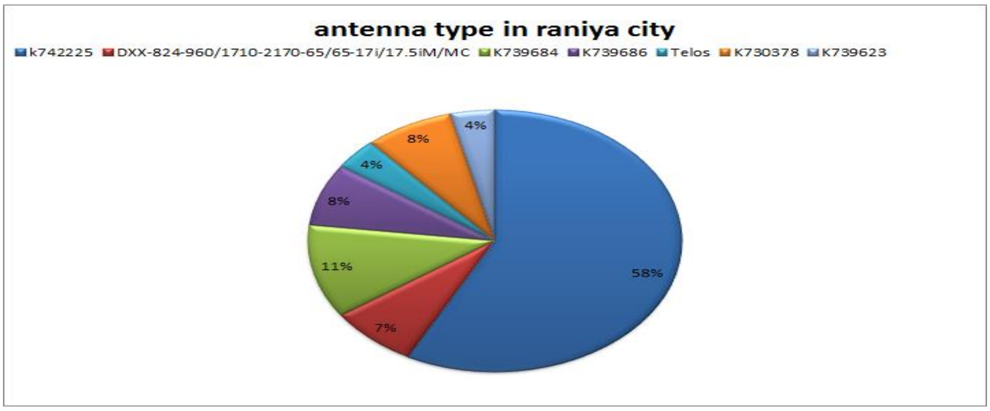

FIGURE 7. The antenna type percent for Rania city

Fig. (7) Show the antenna type percent in Rania region. 58% from Rania area have the k742225. And for K739684 11% and 8% for K739686, K730378 respectively. While 7% for DXX-824-960/1710-2170-65/65-17i/17.5i-M/M-C it's a new type of antenna designed from Huawei Agisson Company. At last 4% for K739623 and Telos. As shown from fig. (8) The antenna type K742225 are favorite for Asia cell due to its good Performance. Also Performance of Huawei antennas is acceptable too. By comparing to Kathrin antenna, the two antennas types have better performance in coverage enhancement and interference control.

The results indicate that both antenna types depend on the network environment and different environments may lead to different optimization results in terms of capacity and coverage performance.

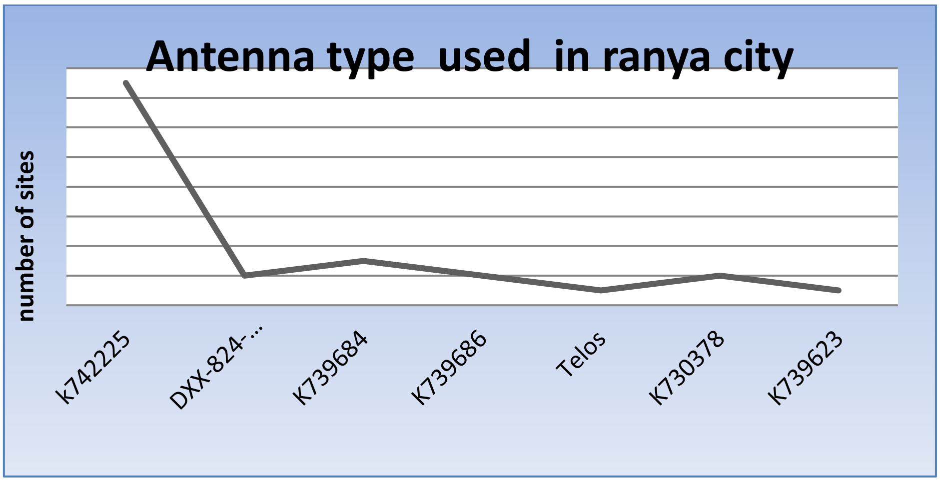

FIGURE 8. The antenna type curve at Rania city

4. CONCLUSION

In this paper the resolution and influence of antenna type Dxx-824-960/1710-2170-65/65-17i/17.5i-M/M-C in Mobile Phone Base Stations in Ranyia City was discussed. System performance results in presence of both Dxx-824-960/1710-2170-65/65-17i/17.5i-M/M-C and Kathrin antenna type were simulated for different sites in raniya city in Kurdistan north of Sulaymaniya. According to the results, Dxx-824-960/1710-2170-65/65-17i/17.5i-M/M-C provides better performance in case of interference limited system, while performance difference is insignificant for noise limited cases. Although Kathrin antenna types scheme is not considered as the best possible for the down tilt scheme, the results emphasize the fact that antenna type *DXX-824-960/1710-2170-65/65-17I/17.5I-M/M-C* should be used, not only to maximize the network capacity, but also to reduce the amount of, e.g., pilot pollution.

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