Camera detection through internet of video sensors

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Abstract: This paper describes the image pattern recognition techniques provided by the internet of things used to observe vehicles as well as the detection techniques used to tie each frame's pattern recognition results together. Adaboost detection and wireless networks are used for video supervision. For wireless system, a camera that can transmit video signal to a receiver or to a wireless router without using any cable in between. The Wi-Fi technologies are used to transfer detection results which are located at the same base station. The experimental results prove the classifiers to be more efficient, and demonstrate superior classification performance of the proposed method, and the WSN frame has simple computational process, which can be easily used in real environments.

Keywords: internet of things; Wi-Fi technologies; Adaboost; object detection; wireless sensor network.

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1 Introduction

Internet of things (IOT) technology, such as ubiquitous networking and pervasive computing, becomes more and more effective for solving intelligent systems related problems, e.g., intelligent security, intelligent transportation, intelligent environmental protection, intelligent logistics, etc. (Luo et al., 2009; Guinard, 2010). Internet of things will connect not only networked terminals like mobile phones, computers, smart devices, but also daily life objects that until now have been to us just 'un-networked things' or 'inert objects'. Entrance into this challenging new era of communication will be possible through combining the evolving technologies and networking frameworks. Internet of things has been envisioned as a forthcoming wave of the world information industry, and it will grow into a trillion-scale high-tech market in several years. Currently, there are many researchers or engineers working in this challenging field, many academic conferences held every year, and many applications and products developed timely.

There are an exceptional number of applications that can make use of the IOT, from home and office automation to production line and retail product detection. The number of applications is endless. In this paper, video-based supervision and detection are mainly discussed which combined with Wi-Fi wireless local area network for transferring results.

Many video detection systems identify objects by virtue of their motion (Li and Zhang, 2004; Sun et al., 2004; Mita et al., 2008). In cases where vehicles are moving quickly past the sensing camera, these motion segmentation techniques are fast and robust. There is a great deal of prior work in the development of video sensor systems (e.g., video cameras DCS, 2006; Rahimi et al., 2005; Kulkarni et al., 2005a, 2005b; Feng et al., 2005; Feng et al., 2003), sensor networks (Culler et al., 2004; Collins et al., 2006; Ke et al., 2005), video streaming (Ljung et al., 2006), energy harvesting, imaging, and image processing (Elgammal et al., 2002; Jodoin et al., 2007; Ishwar et al., 2003; Majumdar et al., 2006). Multiple-target tracking is one such application that can benefit from multiple sensing modalities. Multiple target tracking plays an important role in many areas of engineering such as surveillance, computer vision, network and computer security, and sensor networks (Oh et al., 2007).

Unfortunately, in cases where the sensing camera observes a largely stationary traffic light queue, motion estimation based systems begin to have problems. In these cases, motion segmentation often cannot be used because there is very little motion to be observed. Additionally, long shadows cast by vehicles can cause regions of motion to bleed together into a single large motion segment. Also, inevitable camera vibration can render many motion segmentation algorithms useless, since camera vibration moves the entire image and segmenting the motion of individual cars becomes more difficult. In these problem situations, it becomes necessary to identify vehicles by their appearance rather than their motion.

In this paper, we propose a ubiquitous networking and pervasive computing discriminant function based approach to classify and track combined by internet of things. The rest of the paper is organised as follows: Section 2 describes pattern classifier by Adaboost learning. Section 3 introduces Wi-Fi WSN (Lampropoulos et al., 2008; Xu and Saadawi, 2001) for transferring results obtained by classifiers. Experimental results are presented in Section 4, followed by concluding remarks in Section 5.

2 Pattern classifier

A pattern classifier can be used as a scanner which moves across an input image, classifying a 90 × 100 sub image at each image location, as in Figure 1 and Figure 2.

A simple classifier based on features evaluated with the integral transform consists of:

$$h(x) = \begin{cases} 1 & if\ pf(x) < p\theta \\ 0 & otherwise \end{cases} \tag{1}$$

where h is the classifier, p is the parity, θ is the threshold and f is one of the integral transform-type features discussed above and x is the 90 × 100 sub image. The classifier reports a value of 1 when it believes that a car is found, and it reports a value of 0 when a car has not been found. Training a classifier which uses a given feature f consists of discovering the threshold and parity which maximise its classification performance within the training set (Li and Zhang, 2004).

Figure 1 Training vehicle images (see online version for colours)

Figure 2 Training bike people images (see online version for colours)

Training a set of weak classifiers h_t uses the Adaboost method of varying weights associated with the training set in the following way:

- Given example images $(x_1, y_1),\ldots,(x_n, y_n)$ where $y_i = 0, 1$ for positive and negative examples respectively.
- Initialise weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1,\ldots,T$:

  1 Normalise the weights, $w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$.

  2 For each possible feature, f_j, train a classifier h_j. Find the error for the classifier by evaluating $\varepsilon_j = \sum_i w_i \left| h_j(x_i) - y_i \right|$.

  3 Choose the classifier with the lowest error ε_t.

4 Update the weights: $w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}$ where $e_i = 0$ if example x_i is classified correctly, $e_i = 0$ otherwise, and $\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}$.

- The final classifier is: $h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2}\sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$ where $\alpha_t = \log\frac{1}{\beta_t}$.

Note that the weight associated with each training example is decreased as weak classifiers correctly classify the training example. In this way, as weak classifiers are trained, they are less responsive to training examples which are already 'covered' by previously trained weak classifiers. Also note that the final classifier sums the weak classifiers' results with weights based on the weighted error of the classifier within the training set.

A set of discriminant functions $g_i(x)$, $i = 1, 2,\ldots,c$, where c corresponds to the number of classes to discriminate. Given a feature vector x the decision rule then can be stated as: decide ω_i if $g_i(x) > g_j(x)$ for all $i \neq j$ and the decision boundaries are where ties occur among the largest discriminant functions. For multivariate normal density, the minimum error rate classification can be achieved by the use of the discriminant function given in equation.

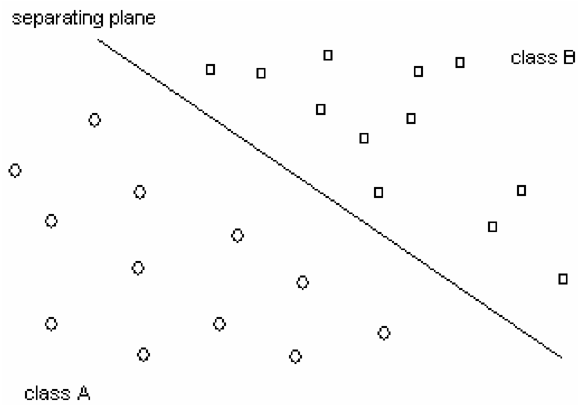
$$g_i(x) = \ln P(\omega_i) - \frac{1}{2}\left((x-\mu_i)^t \sum\nolimits_i^{-1}(x-\mu_i) + d\ln 2\pi + \ln\left|\Sigma_i\right|\right) \tag{2}$$

Taking a general multivariate normal case with different covariance matrices for each category, the resulting discriminant function is given as equation (3):

$$g_i(x) = x^t w_i x + \alpha_i x + \beta_i \tag{3}$$

where $w_i = -\frac{1}{2}\Sigma_i^{-1}, \alpha_i = \Sigma_i^{-1}\mu_i, \beta_i = \ln P(\omega_i) - \frac{1}{2}\mu_i^t\Sigma_i^{-1}\mu_i - \frac{1}{2}\ln\left|\Sigma_i\right|$. The discriminant function is inherently quadratic, which results in decision surfaces that are hyper quadrics.

Figure 3 Two dimensions



If there are two classes of example patterns like vehicle or no vehicle. Each example pattern may be expressed as a vector and placed as a point within a vector space shown below in two dimensions in Figure 3.

If the two classes of example patterns are separable, each class forms its own cloud of points in the vector space and a plane may be drawn between the two clouds of points. New example vectors are classified by evaluating the side of the separating plane on which they lie. Implicit here is the assumption that vectors of the same class lie together in their vector space.

In general, however, the pattern vector space is not limited to two dimensions as shown in the above figure. Say there is an example set $S = \{(X_i, y_i)\}_{i=1}^{m}$. Where X_i is a pattern vector of size n of quantity m, and the y_i are simply labels which indicate the vector's class, $y_i \in \{-1, 1\}$. The classifier then takes the following form:

$$f(X) = X^T AX + b \tag{4}$$

where the elements of matrix A are: $A_{uv} = \sum_{i=1}^{m} \lambda_i y_i x_{iu} x_{iv}$ and x_{iu} means the *uth* element of the *ith* vector X_i. Since A is symmetric, it may be decomposed into $A = \Lambda^T V \Lambda$ where Λ contains the eigenvectors of A and V is a diagonal matrix with the corresponding real Eigen values along the diagonal.

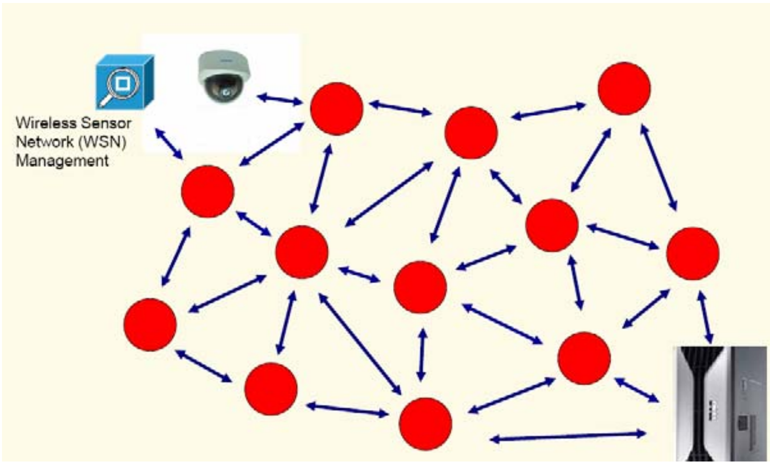
3 Wi-Fi WSN feame

Wi-Fi provides service in private homes and offices as well as in public spaces at Wi-Fi hotspots set up either free-of-charge or commercially. Organisations and businesses, such as airports, hotels, and restaurants, often provide free-use hotspots to attract or assist clients. Wi-Fi allows cheaper deployment of local area networks (LANs). Also spaces where cables cannot be run, such as outdoor areas and historical buildings, can host wireless LANs.

Wireless range-extenders or wireless repeaters can extend the range of an existing wireless network. Strategically placed range-extenders can elongate a signal area or allow for the signal area to reach around barriers such as those pertaining in L-shaped corridors. Wireless devices connected through repeaters will suffer from an increased latency for each hop (Lin et al., 2009; Khoukhi and Cherkaoui, 2010; Dua et al., 2010). Additionally, a wireless device connected to any of the repeaters in the chain will have a throughput limited by the 'weakest link' between the two nodes in the chain from which the connection originates to where the connection ends in Figure 4.

The video sensors are based on ten AV8185 cameras attached to OpenBrick-E Linux embedded PCs. The detection algorithm is implemented using OpenCV (open source computer vision) library. Our detection algorithm implementation runs at 12 frames per second and 800 × 600 pixel resolution. The distance between cameras is 8 metres. If a change is detected, a video stream from the node will be transmitted to the gateway using standard video compression techniques (e.g., MPEG-4 or H-264).

Figure 4 Wireless local area networks (see online version for colours)



Like with different wire-free tech, wire-free security camera systems are normally more or less low-cost. An amount only make it costlier would be the high-end features incorporating the lenses utilised and challenging engineering getting carried out. Nonetheless all they are worthy of to pay since these give one difficult features incorporating crisp image top quality, networkability, flexibility (operates in fact in full darkness), and the perfect probable security.

Apart from that, supervision camera wire-free is in fact even more trustworthy weighed against usual hardwired. Remaining wire-free, culprits and culprits won't be capable to identify in fact getting watched as zero wiring in any respect implicated. Wi-Fi supervision camera responds the fundamental issue with wired supervision camera; hooking up wire links which a wired photographic camera utilised might be simply snipped off and so the objective of setting up such security appliances is in fact overcame. Also, the actual mobility on the subject of supervision camera wire-free lets one push the button in the outside and indoor.

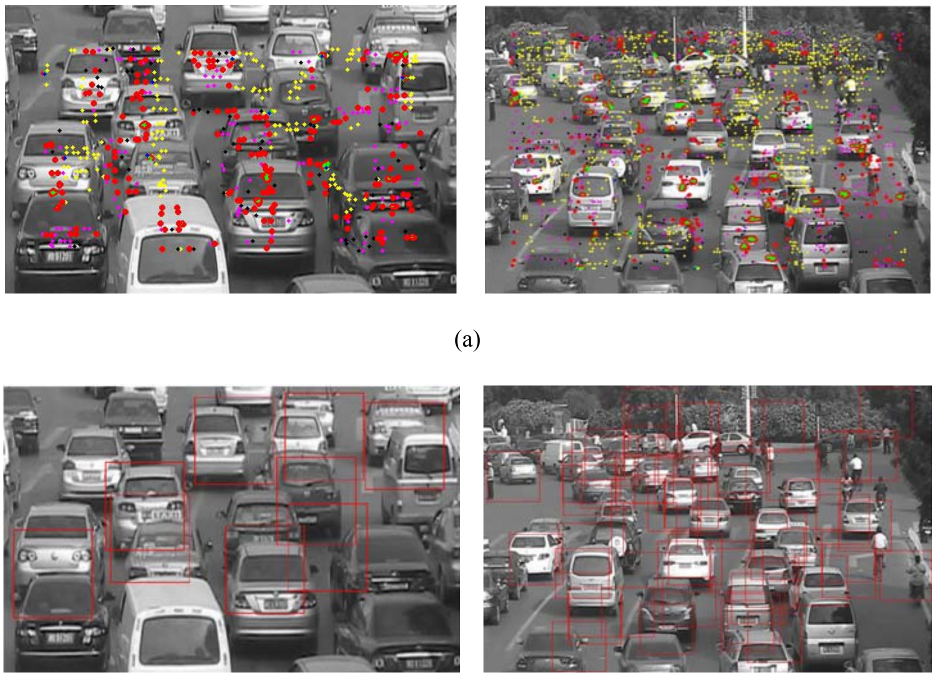
Figure 5 Wi-Fi wireless camera framework (see online version for colours)

A set of infra-camera now proffers the system capacity just as the IP-based photographic camera showed in Figure 5. There's in addition supervision camera wire-free tough-wired such that actions could be established plus a notifying interaction could be sent to the security alarms. Even though every single one of these wire-free security camera systems may perfect supply the security.

4 Experimental results

The experiments were carried out for car-rear detection on video clips taken in various conditions. The training was done using 100 positive and 100 negative samples. In Figure 6(a) shows that different color points stand for different camera regions; Figure 6(b) shows vehicles and bike 0 people detection. After a frame is scanned, some locations within the image are suspected of being vehicles or bike people. The method presented of measurements gives a higher priority to high-confidence measurements, and it seeks to avoid a situation where a track is updated with the closest measurement without regard to the measurement's confidence. In these actual traffic situations recognising a vehicle is difficult, even for a human, without significant amounts of context on either side of the vehicle. But as seen from Figure 6, that our method still yields higher classification performance.

Figure 6 Detection results of wireless cameras (see online version for colours)



(a)

(b)

Table 1 shows detection accuracy for all the tracks to compare different detecting approaches. In the video, many tracks with multiple moving vehicles in the sensing region were recorded during the experiment. Most of them had vehicles moving in the same direction. Only a few tracks included multiple vehicles crossing each other.

Table 1 Average detection accuracy

Method	*Recall rate (%)*	*Accuracy (%)*
Block matching	73.5	81.0
Gaussian mixture model	86.3	90.2
Simple Adaboost detection	91.7	96.8
Our method	95.7	97.1

Also, the WSN can be a powerful tool for collecting and communicating data between cameras and the platform (host of application), as long as the platform is within range of the WSN. The link between these networks is an access gateway. Each access gateway in the IOT network will have access to the database server, thus every device would be connected and information from the entire network aggregated at the database server.

5 Conclusions

As cameras can see infinite, therefore it all depends on the size of the object. Wider the angle of the lens, smaller it will appear but area coverage will be greater. A quadratic discriminant analysis based approach is presented which leads to hyper-quadric boundary between the object class and clutter class, thus realising multiple thresholds based weak classifiers. Digital motion detection is a feature for our self recording all-in-one cameras. Experiments show that the proposed method yields higher classification performance and has better performance than other related systems.

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