An Advanced Approach on Detecting and Recognizing Objects

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***Abstract*— Object detection and recognition is an important area of research in Robotics using Artificial Intelligence. Finding the distance to and estimating the size of detected object is also interesting in certain applications. Hence, Arduino micro-controller board with 2 Maxbotix Ultrasonic Sonars on a Robot are used to measure distance and direction to an object. A robot with a mounted camera as it moves in its environment and encounters an object at specific distance away from the object snapshots of the object are taken. Therefore, in order to validate proposed approach, stored image templates of an object are compared with the snap shots taken to recognize and identify it. Consequently, correlation method is employed to track and recognize the objects encountered by the robot. Thus, for a moving object the Kalman filter is used to track an object and Log-Polar Phase correlation method is used for recognition. Finally, results have shown that such algorithms is valuable in areas such as surveillance, security, and knowledge.**

Keywords- Arduino; Kalman filter; log-polar; sonar; phase correlation.

I. Introduction

Robots are increasingly using Artificial Intelligence in surveillance systems, factories, hospitals, guided systems. Autonomous mobile robots can move around and gather information about the environment. Artificial vision requires fast processors in order to run real-time vision-based algorithms. Sensors used for navigation include sonar sensors, infrared sensors, and laser range finders. Infrared sensors are used for proximity detectors and have limited range. Laser range finders are expensive however have excellent range accuracy and reliability. Sonar sensors are reasonably priced and are more commonly found in robots. The sonar sensor measures the distance to an object by transmitting frequency in the ultrasonic frequency range. The beam width is wider than the laser beam. Robots mounted with cameras and sonars offer a higher reliable capabilities. Cameras are considered passive sensors while sonar sensors are considered active sensors. Tracking objects is a well researched area [1].

In certain applications it is desired to detect, track, and recognize an object. Recognition of an object is a very challenging problem and feature based methods can be used [2]. Variety of methods exit in the literature for object tracking [1] each having strengths and weaknesses. Some of the common tracking algorithms are blob tracking, contour tracking, feature matching, kernel base tracking, and particle filter tracking. For objects moving behind obstructions, the Kalman filter and Particle filter are very practical. Objects being tracked may be deformable (e.g. human movement) or non deformable (e.g. rigid objects vehicles).

The Scale-invariant feature transform (SIFT) algorithm is used in computer vision to detect and describe local features in images [3]. The algorithm first works on a training image and extracts feature descriptions of an object. The algorithm has proven to perform well even under image scale, noise and illumination. Another algorithm used in computer vision is the Kanade-Lucas-Tomasi (KLT) feature tracker [6]. The KLT algorithm falls in the category of optical flow and is faster than traditional techniques. The KLT algorithm has performed well in object tracking in videos. In this paper, the Kalman filter [11],[12] is used to track an object and Log-polar phase correlation [13],[16] is used for object recognition [17]. The main contribution of this paper is to devise a procedure for object recognition either stationary or in motion. Study is performed for two scenarios, in the first case, the camera is moved around while the object is stationary and in the second case, the camera is stationary and the object to be recognized is in motion. Applications of the presented methods may find useful in areas such as surveillance, security, and knowledge. Another application is in devices for the blind people. The blind people often have hard time locating miss-placed objects in a room. In such cases, cameras mounted on robots or ceilings take a top view snap shots of the room. As now a days the processors have fast processing capabilities and correlation methods once considered time consuming can now be used in real-time.

The paper is organized as follows, in Section II, the methods are presented. In Section III, experimental setup is presented and in Section IV results and discussions are presented and finally in Section V, conclusion and future directions are given.

II. Methods

A. *Distance and size of an object*

There exists a relation between distance to an object and size of an object in an image. The distance to an object can be calculated as an object's apparent angular size is directly related to its actual size. The following equation holds for objects

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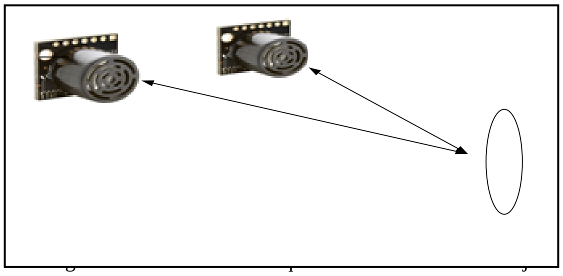
which are far away, Object Dist = (size of object/ angular size in degrees) x 57. The other more common method used is the triangulation.

Ultrasonic sensors can be used to find direction and distance to objects. Two sensors are required to get the direction to an object. With two sensors the steering toward the object becomes easier and when the range values read from the two sensors have equal values (i.e. D1=D2) then the direction to the target is achieved. If the left sensor value read is higher than the value read from the right sensor. Then to adjust the track the movement of the robot would be forward and turn right so the two values from each sensor match.



B. Kalman Filter

T The Kalman filter (KF) is named after Rudolph E. Kalman, who in 1960 published a paper describing a recursive solution using state space methods [11]. The Kalman filter is a predictor-corrector type of estimator and is optimal in minimizing the estimated error covariance. The Kalman Filter has been used in numerous applications, in particular in the area of autonomous or assisted navigation. The Kalman filter is an estimator used to estimate the state of a linear dynamic system corrupted by Gaussian white noise. The Kalman filter provides the estimate of a discrete-time controlled process of a linear stochastic difference equation

$$\hat{x}_{k|k-1} = A_k \hat{x}_{k|k-1} + B_k u_k + w_{k-1} \quad (1)$$

and a measurement is given by

$$z_k = H x_k + v_k \quad (2)$$

where $\hat{x}$ is the estimated state, A is the state transition matrix, u is the control variables, B is control matrix, and H is measurement matrix. The random variables w and v_k are assumed to be independent, Gaussian white noise, represent the process and measurment noise, respectively. It is important to note, in general, the matrices A, B, and H are time dependent, however, in our experiments they are assumed to be constant [17].

The Kalman filter consists of two parts, the filter estimates the states at time k and then obtains a noisy measurement feedback. The two parts of the Kalman filter are given below as, the predictor and the measurement or correction feedback:

Predict (process time update equations):

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$$\hat{x}_{k|k-1} = A_k \hat{x}_{k|k-1} + B_k u_k \quad (3)$$

$$P_{k|k-1} = A_k P_{k-1|k-1} A_k^T + Q_k \quad (4)$$

Equation (3) is the predicted (a priori) state and eq (4) is the predicted (a priori) estimate covariance.

Update (measurement or correction update equations):

Feedback

$$\hat{z}_k = y_k - H_k \hat{x}_{k|k-1} \quad (5)$$

$$S_k = H_k P_{k|k-1} H_k^T + R_k \quad (6)$$

$$K_k = P_{k|k-1} H_k^T S_k^{-1} \quad (7)$$

$$\hat{x}_{k|k-1} = \hat{x}_{k-1|k-1} + K_k \hat{z}_k \quad (8)$$

$$P_{k|k} = (I - K_k H_k)\, \mathrm{P}_{k|k-1} \quad (9)$$

where P is the state variance matrix, Q is the process variance matrix, y measurement variables, K is the Kalman gain, and R is measurement variance matrix. Equation (5) is called the innovation or measurement residual, eq (6) is the innovation (or residual) covariance, eq (7) is called the Kalman gain, eq (8) is the updated (a posteriori) state estimate and eq (9) is the updated (a posteriori) estimate covariance.

C. Correlation Methods

Correlation filters are well known signal processing techniques which have been used in object detection and recognition problems. Correlation filters have been used in various fields of applications such as biometrics iris, face, palm, fingerprint, and voice recognition, in areas of military, such as automatic target detection, missile guidance, in the area of health, such as medical imaging applications.

Phase correlation method is used to check the similarity of two images with equal size. The phase correlation method is used for template matching, motion estimation, image registration, and object tracking. The phase correlation method has been used in image registration. In [10],[13],[17] it has been shown a scaled, rotated, and translated image can be recognized.

Let g(x,y) and h(x,y) be two images each of size L x W. Denoting their 2D Discrete Fourier Transforms (2D DFTs) as G(u,v) and H(u,v). The cross power spectrum $R_{GH}(u,v)$ of $G(u,v)$ and $H(u,v)$ is then given by

$$R_{GH}(l,m) = G(l,m)\, H^*(l,m) \quad (10)$$

D2

D1

where * denotes the complex conjugate. The normalized cross power spectrum $R_{GH}^{N}(l,m)$ between the two images g(x,y) and h(x,y) is defined by

$$R_{GH}^{N}(l,m) = \frac{G(l,m)H(l,m)*}{|G(l,m)H(l,m)*|} = e^{j\theta(l,m)} \tag{11}$$

The phase correlation function $r_{GH}^{N}(p,q)$ is the 2D inverse DFT of (11) and is given by

$$r_{gh}^{N}(p,q) = \frac{1}{P \cdot Q} \sum \sum R_{GH}^{N}(l,m) W_P^{-lp} W_Q^{-mq} \tag{12}$$

Suppose, in the case g(x, y) and h(x, y) are the same image then the Phase Correlation function is given by

$$r_{gg}^{N}(p,q) = \frac{1}{P \cdot Q} \sum \sum W_P^{-lp} W_Q^{-mq} = \delta(p,q) \tag{13}$$

where $\delta(p,q)$ is the Dirac delta function. The peak point location is given by

$$\delta(x,y) = \max_{(x,y)} \{r^N\} \tag{14}$$

In the case where the two images are same then their Phase Correlation function gives a distinct sharp peak. The peak height is used to measure the similarity between two images. The Phase Correlation function has the following properties, shift invariance, amplitude invariance, and immunity against additive noise. The properties can be verified directly from the Fourier Transform's properties [8],[17].

If the two images are related to each other by only a pure translation such as

$$g(x,y) = h(x-x_0, y-y_0), \tag{15}$$

that is g(x, y) is translated by an offset (x_0, y_0). In this case, from the Fourier transform shift theorem, the two images only differ in a phase shift,

$$G(u,v) = H(u,v) e^{-j(ux_0+vy_0)}. \tag{16}$$

From the normalized cross-power spectrum the exponential phase shift factor can be obtained as,

$$P(u,v) = \frac{H(u,v)G^*(u,v)}{|H(u,v)G^*(u,v)|} = e^{j(ux_0+vy_0)}. \tag{17}$$

The inverse Fourier transform of the phase difference denoted by $p(x,y)$ gives the Dirac delta function at the offset (x_0, y_0),

$$p(x,y) = \delta(x-x_0, y-y_0). \tag{18}$$

In case, g(x, y) is a scaled, rotated, and translated version of h(x, y), defined as,

$$g(x,y) = h(s\cdot x\cos\theta - s\cdot y\sin\theta - x_0, \; s\cdot x\sin\theta + s\cdot y\cos\theta - y_0) \tag{19}$$

Taking the Fourier transform results in,

$$G(u,v) = \frac{1}{|s^2|} H(u'\cos\theta - v'\sin\theta, u'\sin\theta + v'\cos\theta) \cdot e^{-j(ux_0+vy_0)} \tag{20}$$

where u' = u/s and v'= v/s. The magnitude of above (20) is

$$M_G(u,v) = w \cdot M_H(u'\cos\theta - v'\sin\theta, u'\cos\theta + v'\sin\theta)) \tag{21}$$

where w is a weighting factor. Using polar coordinates (r,ϕ) and letting $u = r\cos\phi$ and $v = r\sin\phi$. Inserting in (21) above results in,

$$M_G(u,v) = w \cdot M_H(r'\cos\phi\cos\theta - r'\sin\phi\sin\theta, \; r'\cos\phi\sin\theta + r'\sin\phi\cos\theta) \cdot \tag{22}$$

and using trigonometric identities results in

$$M_G(u,v) = w \cdot M_H(r'\cos(\phi+\theta) - r'\sin(\phi+\theta)) \tag{23}$$

which can be represented as,

$$M_G(r,\phi) = w \cdot M_H(r', \phi+\theta). \tag{24}$$

Converting to log-polar form, by taking the logarithm results in

$$M_G(\log r, \phi) = w \cdot M_H(\log r', \phi+\theta) \tag{25}$$

where $r' = r/s$ and $\log r' = \log r - \log s$. From the Fourier properties, a positional shift produces a phase shift and linear scaling of a spatial variable x, y produces an inverse scaling of spatial frequencies u, v. The phase-correlation method can be used to obtain the translation in log-polar coordinate system. The algorithm to perform distributed Phase Correlation can be used to check if two images match or not.

The above also goes by the name of Fourier-Mellin transform which is used to register images that are misaligned due to translation, scale, and rotation. The procedure can be performed in parallel as follows, use the Fourier transform to recover translation. Applying the log-polar transform to the magnitude spectrum, the scale and rotation is recovered by using phase correlation. The recovery is possible since the scale and rotation in Cartesian domain becomes a pure translation in the log-polar domain

III. Experiment Setup

A sonar, a camera, sd card, and arduino micro-controller board were used in the experiment setup. The sonars were used to measure range to an object and camera was used to take snap shot of an object. Matlab 2013 was used to run the Kalman Filter and Phase correlation simulations.

Sonar sensors are used in a variety of applications such as autonomous navigation, large object detection for example human movement, landing flying objects, and educational and hobby robotics. Sonar sensors are ultrasonic sensors using the high frequency of 42 kHz. The sensor is not affected by the color or other visual characteristics of the object. These sensors transmit sound waves which bounce off the object and surroundings. The time of flight to and reflected off the object is used to calculate the range or distance to the detected object.

The LV-MaxSonar-EZ sensor used in the experiment has the capability to operate independently under the user's control. This sensor has three separate outputs that update the range data simultaneously. They are the Analog Voltage, Pulse Width, and RS232 Serial.

The LS-Y201 is a serial port camera module. It captures high resolution pictures using the serial port in JPEG format. It can be used in variety of applications such as image capture systems, environmental monitoring, industry monitoring, medical equipment, video phone, security, and vehicle based GPS.

The Arduino Uno is open-source microcontroller board based on the ATmega328. It has 14 digital input/output pins, a 16 MHz ceramic resonator, 32k flash memory, a USB connection, a power jack, a reset button and an ICSP header. It connects to the computer through the USB cable. The development environment implements the processing / wiring language.

The Arduino has 512 bytes EEPROM and 1024 bytes of RAM. To get more storage, a secure-digital SD-card can be used. It can hold a few gigabytes of storage for data logging.

Figures 2 to 4 below show the devices and circuit diagrams showing the wiring to Arduion board.

Fig 2. Sonar from Maxbotix.

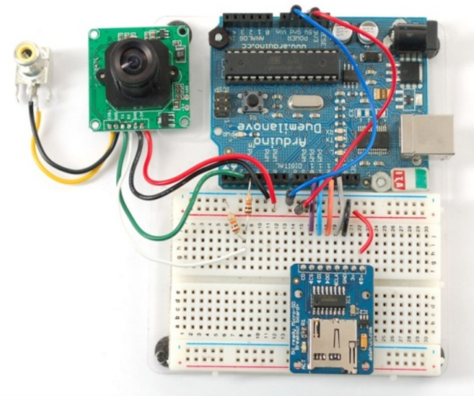

Fig 3. Arduino board with camera and sd card.

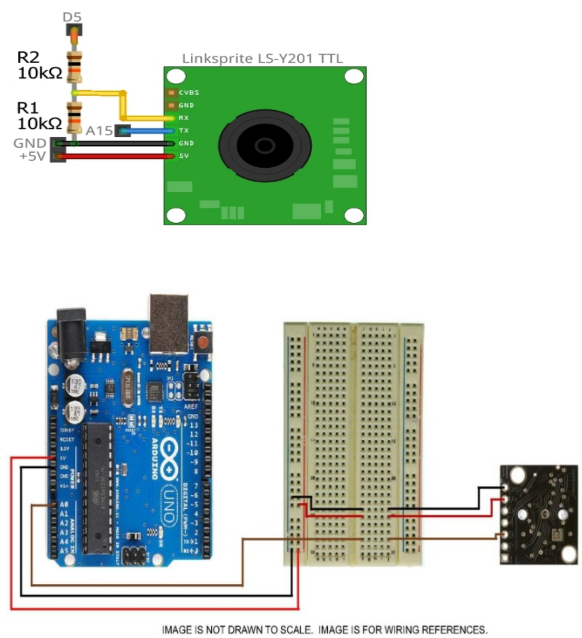

Fig 4. Arduino board with camera.

IV. Results and Discussions

A. Moving Robot and Stationary Object

An example of moving robot and stationary object is the scenario of an autonomous car moving and recognizing road signs. In such a case, as the robot moves in its environment and an object is detected. It calculates distance to the object and as it steers toward an object from a predetermined distance of 1.5 foot (other preset distance maybe used depending on sonar or infrared sensors range) a snapshot of the object is taken. The snapshot is compared with templates in a database of images. If the two images match based on a value larger than the threshold, then a positive match is declared, otherwise if the value is less than the threshold a mismatch is declared.

Algorithm 1: Robot mounted with a Camera and Sonar Steps:

1) Object is detected and distance calculated
2) If (distance equals 1.5 foot) take a snapshot.
3) Compare snapshot with database of images.
4) If (snapshot same as image template) then declare a match and image is recognized otherwise no match.

Fig 5. An example of two objects detected and desire is to recognize the object located on the right.

Fig 6. Templates of objects stored in the database.

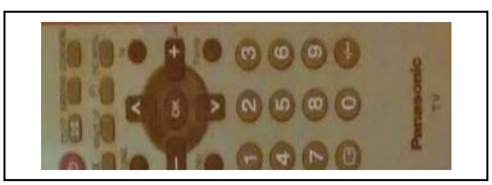

Fig 7. Template of remote control.

Fig 8. Object recognition based on feature image template.

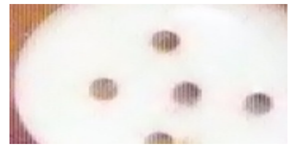

Fig 9. Object recognition based on feature image template differentiating pepper from salt holder.

Fig 10. Object recognition based on feature image template.

Another scenario is to search and to detect a specific object among multiple objects, as an example is to detect the pepper holder and not the salt holder. In such a case, differentiating feature image template is used as shown in Fig 8 to discriminate between the salt and pepper holder. Image templates with unique features are the ones most suitable to be stored in the database and used in matching. In Table 1 the results are tabulated for which objects were recognized and not recognized. It is seen the more distinct features an object has the higher the probability of recognition of the object. Note in our experiments the template objects did not have the same orientation, or scale as the objects depicted in Fig 8. In case the templates are formed from the same image, the phase correlation gives a very sharp peak and 100% accuracy in object recognition. The challenge comes when the reference image and object have different orientation, scale, and translation. In our experiments, the object orientation was larger than 60 degrees and scales larger than 2. Through numerous experiments with variety of objects, a reasonable threshold value of Th=0.007 was chosen as a threshold. The choice for threshold value is critical to the success of object recognition. For example knowing the reference image is a cropped version from a snap shot image, then the value of Th would be in the high range of 0.1 to 0.4, however if the reference image was taken from a different range and orientation, then generally the value of Th would be much lower. Further research is necessary to see if a global Th could be found. A value larger than Th was considered a match and therefore recognition concluded. In Table 1, the results are presented of objects being recognized under large orientation and scale. Note, in all cases there were distinguished peaks however the peaks were below the threshold and therefore for these objects recognition was rejected. The scale factor was a major issue in our experiments which resulted in poor performance. As it is well known, the scale of an image is a function of distance, and the camera's properties, such as focal length and resolution. In our experiments, all reference images of isolated objects had been taken from a predetermined distance of 1.5 foot and snap shots were taken of top view. In order to minimize the scale difference of snap shot taken by the robot and the reference image, the robot was made to steer toward an object so the distance acquired by sonars was 1.5 foot from the object before a snap shot was taken. By having robot taking a snap shot of an object from exactly the same distance as the reference images were taken and done so by the same camera reduces the chances of having a large difference in the scale of the two images. For a small scale difference less than a factor of 2.0 and rotation angle less than 40 degrees, all images were recognized.

Because there are infinite views from which snap shots of an object can be taken, it is desirable to use a priori knowledge in the settings of the camera and distances used to capture reference images. Robots having the knowledge of the reference settings will aid in mimicking the settings such as distance and taking top view snap shots, therefore, recognizing the objects. For example, a robot taking a side view snap shot of an object and the reference image being a top view of the same object will never match. Also, not knowing the range of the camera to an object nor its properties would result in large scale differences and poor recognition of detected objects.

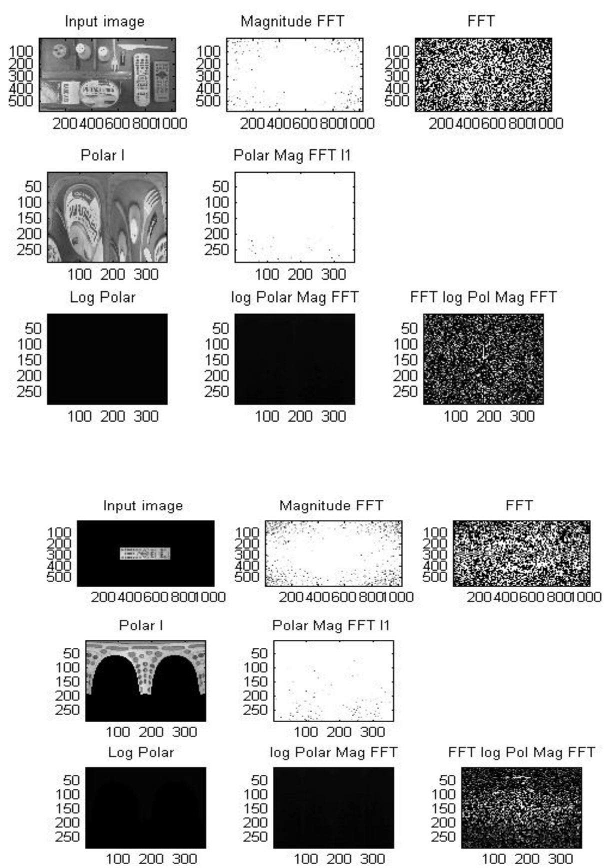

Fig 11. Remote control recognition based on feature image template.

TABLE I. TEMPLATE OBJECTS WITH LARGE ORIENTATION AND SCALE.

	Image with Multiple Objects	Recognition
1.	Salt holder / pepper holder	yes
2.	Knife	no
3.	Fork	no
4.	Cheese	no
5.	Bandaid	yes
6.	Battery duracell	yes
7.	Ruler	no
8.	Blue pen with red	no
9.	Remote control satellite	yes
10.	Remote control tv	yes
11.	Blue cap with colored pins	no

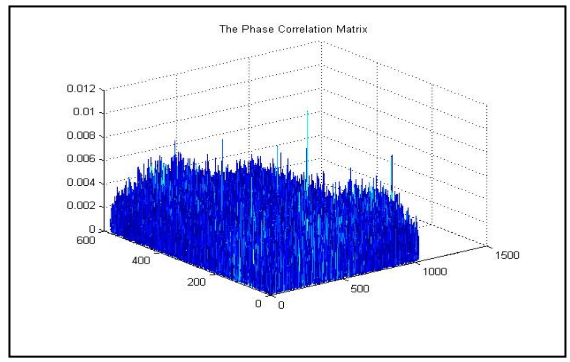

Fig 12. Highest peak shows where the remote control matches.

B. *Stationary camera and moving objects*

An example of stationary camera and moving objects is the scenario of a surveillance system tracking objects. In such a situation it is desired to recognize a moving target among other moving objects. In this type of problems, the Kalman filter is used to track the moving target from time to time (or frame to frame) [17] . After every say, 5 or 10 frames, the tracked target is compared to the reference object (stored template) and if the two match then a positive match is declared, concluding the target has been recognized otherwise a negative match is declared.

Algorithm 2: To track and distinguish moving objects:

Steps:

1) Blob or object detection using background subtraction.
2) Gaussian filter
3) Threshold
4) Obtain the centroid
5) Kalman filtering for tracking
6) Phase Correlation for recognition

Fig 13. Object recognition based on feature image template.

In Fig 13 the blue cap with colored pins is detected and recognized. Note, the movement of the objects was slow as not to cause any blurring of the image. If objects are moved faster than the camera capture rate blurring occurs and results in very poor recognition.

V. CONCLUSION AND FUTURE WORK

In this paper, we have shown how robots can use artificial intelligence to recognize stationary objects or moving objects.

Sonar sensor was used to steer the robot to a predetermined distance from the object and a snapshot of the object taken is compared to reference object (template stored in database). It is seen object in an image gets scaled as a function of distance and camera properties. Having knowledge of the distance to an object the proper reference images with similar settings are retrieved from the database and comparisons made. It is seen the log polar phase correlation method is very reliable for object recognition even to such a degree to distinguish the buttons on a remote control. On the other hand, moving objects can be tracked by Kalman filter and a targeted object recognized under the condition there is no or small deformity. Multiple objects can be tracked by using a bank of Kalman filters in parallel. Further research is necessary to devise algorithms having high accuracy for objects with deformity.

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