A Survey on Sensors for Autonomous Systems

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***Abstract*—This paper presents a survey on state-of-the-art sensors for autonomous systems. The key performance parameters along with the operating principle of sensors used in autonomous systems are thoroughly explored. Practical aspects such as performance parameters, sensor output data format, sensor interfaces, size, power consumption, compatible hardware platforms, data analysis, and signal processing complexities are summarized. Such information serves as a practical guide for designing smart sensing systems for autonomous systems.**

Keywords—Sensors, ultrasound sensor, mmWave sensor, thermal camera, mmWave Radar, LiDAR, automotive camera, SLAM, autonomous systems.

I. Introduction

It is evident that there exists no single sensor which meets all the strict requirements for the safe, secure and reliable operation of fully autonomous systems such as autonomous robots, autonomous vehicles on the road and unmanned aerial vehicles (also popularly known as drones) in low-altitude space corridors. In many cases, multiple sensors such as ultrasound sensors, Infrared (IR) sensors, camera modules, Radar modules, Light detection and ranging (LiDAR) modules, microelectromechanical systems (MEMS), thermal cameras and localization sensors such as global positioning system (GPS), Accelerometers, Gyroscopes, and camera-based visual simultaneous localization and mapping (VSLAM) need to be integrated for such fully autonomous systems [1]. Individual sensors fail strictly to produce a reliable and detailed image of the surrounding environment for the autonomous systems in adverse weather conditions such as heavy rain, snow, fog, and dust. Though LiDAR is one of the attractive solutions to finding a 3D map of the surroundings, it still needs to overcome several open challenges such as cost reduction, miniaturization, weight reduction, more channels for higher resolution and complete information of the dynamic objects in the image with low computational cost and minimum latency [1].

Ultrasound sensors are short-range sensors that give the range of the object without giving much insight into the object itself. These are typically used for closer object detection for example in parking assistance. Operating frequencies are in the range of a couple of tens of kHz (for example 58 kHz) [2]. In addition, the adversary can easily cause the ultrasound sensors to behave abnormally when these are blocked and/or interfered with by other ultrasound sensors nearby [3]. Though these are cheaper but alone do not solve challenging requirements of fully autonomous vehicles.

Vision-based sensors such as cameras give detailed information compared to ultrasound sensors but these are not robust enough for adverse weather conditions, low light conditions such as night, fog, snow, and heavy rain. Detection of objects in the short-range is another limitation. IR cameras can be integrated with cameras to solve some of these challenges up to some extent such as night vision. Though a machine learning-based approach to train the model with images for object detection and classification, traffic sign recognition is well matured still, these alone are not good enough for fully autonomous systems in adverse weather conditions [4].

Radars detect the range, velocity, and angle of arrival of the objects in its field of view (FOV). There are mainly two types of Radars, namely, (a) Pulsed Radar and (b) Frequency modulated continuous wave (FMCW) Radar. Pulsed Radars are conventional Radars and range is calculated by using the time delay between transmitted and reflected pulses. On the other hand, FMCW Radars transmit a frequency modulated continuous wave and reflected FMCW signal is mixed with transmitted FMCW signal to generate an intermediate frequency (IF) signal, which is used in calculating the range. FMCW Radars operating in 77-81 GHz, field of view and beamwidth can be set from a few degrees up to about 110° by careful antenna design and selection. These Radars cover the range from a few meters up to 300 meters [5]. Multiple devices can be used to reach the 360-degree view. These are robust and penetrate fog, snow, and dust but give the only range, velocity and angle of the objects without the detailed image with features of obstacles.

Laser-based light detection and ranging sensors (LiDARs) are similar to radars operating at much higher frequencies that enable them to produce a high-resolution detailed map of the surrounding. The main advantage is the ability to create a precision 360°- and 3D image that is very desirable for object detection. But these are highly expensive and need to overcome several challenges mentioned earlier to be able to use in autonomous vehicles.

Localization sensors such as GPS, which determines the position based on GPS/GLONASS satellites especially in the outdoor environment. An accelerometer measures the acceleration in all three axes. Gyroscope is used for measuring angular velocity. VSLAM is used for localization, mapping, and navigation [6].

The remaining sections of this article are organized as follows: Section II describes the state-of-the-art sensors and their performance metrics, section III discusses the

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interfacing of sensors and computing platforms for sensors and section IV describes the data analysis and/or machine learning techniques for autonomous systems and finally conclusion in section V ends the article.

II. Sensors for autonomous systems

A. Ultrasonic Sensors

The Ultrasonic sensors use sound waves to calculate the range of an object using time of flight (ToF), which is the round trip travel time from a sensor to an object [2][7].

As shown in Fig. 1, an ultrasonic sound wave is transmitted then the time (t) taken by it to return is used for range (x) calculation.

$$x = \frac{1}{2} \cdot c \cdot t$$

$$c = c' + 0.6 * T$$

here, c'= 331 m/s and c is the speed of sound waves at temperature T(°C) .

Before summarizing the key performance metrics of the ultrasound sensors in Table 1, a brief overview on hardware platforms is presented. Computing and/or hardware platforms are classified into three categories, 1) Microcontroller unit (MCU) based platforms, for example arduino [8], 2) Microprocessor unit [MPU] (including operating system (OS)) based platforms, for example platforms from Raspberry Pi [9], and 3) Field programmable gate array (FPGA) based platforms, for example platforms from xilinx [10].

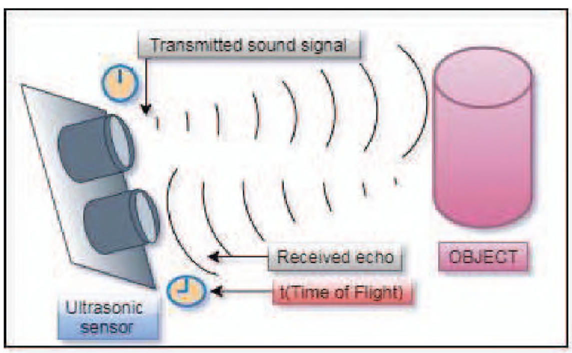

Fig. 1. Principle of ultrasonic sensors based distance calculation.

TABLE I KEY PERFORMANCE PARAMETERS OF THE ULTRASONIC SENSORS [11][12].

Nominal range of sensing parameter	Nominal sensor operating frequency	Interfacing & compatible computing platforms	Sensor output data format
20 cm (min) 2-10m (max)	40-70 kHz	I2C, RS232, USB, UART for interfacing All three MCU, MPU & FPGA based platforms	Analog voltage, Analog envelope, Pulse Width,

B. CAMERAs

VSLAM

VSLAM is the process by which an autonomous system builds a map of the environment and at the same time uses this map to compute its location using vision based sensors (for example camera). It calculates it's position through the spatial relationship between itself and multiple keypoints (shown in Fig. 2). Visual information is obtained using visual sensors such as monocular cameras, stereo cameras and RGB-D cameras etc. and then keypoints are detected using Binary descriptors such as BRISK, ORB, BRIEF. Monocular cameras are preferred in SLAM systems because of simple hardware requirements, lower cost and smaller form factor. For consistent mapping, SLAM algorithms generally use three different approaches: Extended Kalman filter (EKF), Particle filter (Fast SLAM) and graph-based SLAM [6].

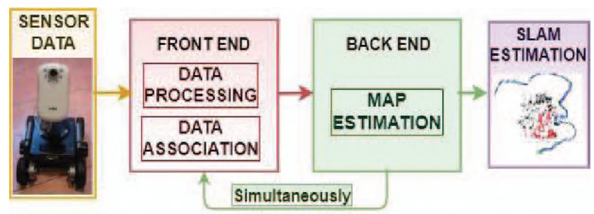

Fig. 2. Architecture of visual SLAM system

MEMS thermal cameras

MEMS camera is a non-contact temperature measurement sensor. A MEMS thermal camera has two main parts as shown in Fig. 3. One is the silicon lens and the other one is the thermopile sensor.

The radiant heat of far-infrared rays emitted from objects is focused on the thermopile sensor using a silicon lens [13]. The thermopile sensor produces electromotive force as per the incident radiant energy of far-infrared rays. Using the produced electromotive force and the internal thermal sensors, the temperature will be measured in a non contact manner.

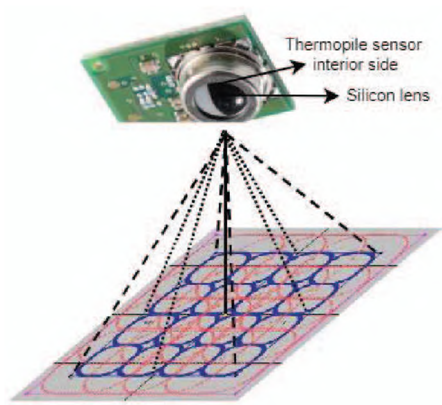

Fig. 3. Principle of MEMS Thermal camera [13].

As shown in Fig. 4, MEMS Thermal camera gives temperature data of the measurable area in terms of pixels. For example, D6T-32L-01A (1024 channels) [13] has 1024 pixels. This temperature data along with artificial intelligence techniques and customized software can be used to distinguish between different objects such as humans, animals, and appliances. Using machine learning and deep learning techniques, the accuracy of such determinations can be improved autonomously. It is important to note that measurable area increases as the distance of the objects increases from the sensor. If the object's area does not cover substantially considerable number of pixels then it is very likely that it will not get detected. Key performance parameters of MEMS Thermal cameras are tabulated in Table II.

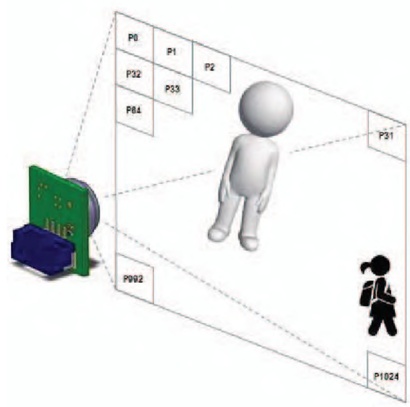

Fig. 4. Temperature data of pixels for D6T-32L-01A (1024 channels) [13].

TABLE II KEY PERFORMANCE PARAMETERS OF THE MEMS THERMAL CAMERAS [12]

Sensing parameter	Compatible computing platforms	Interfacing	Sensor output
Distance: up to 6 m	All three MCU, MPU & FPGA based platforms	I2C interface	Digital I2C & 2051 bytes for D6T-32 L-01A (1024ch)

C. LiDAR

LiDAR is a noncontact range-finding technique that uses either the time-of-flight (t_{oF}) or FMCW for range measurement. An optical signal is projected onto the target and the backscattered signal is detected and processed to

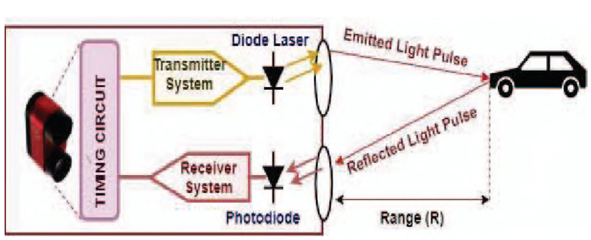

Fig. 5. : Working principle of ToF LiDAR.

determine the range using time delay. Further using the scanning technique, a 3D point cloud is created of the target unit or surrounding.

Based on the measurement principle, LiDARs are classified as [14]:

a. Pulsed Lidar

Pulsed Lidar is based on the ToF principle where an optical signal pulse is used and hence range (R) can be calculated as.

$$R = \tfrac{1}{2}.c.t_{oF},$$

where c and t_{oF} is the velocity of light in vacuum and time of flight respectively.

b. Continuous Wave Amplitude Modulated (CWAM)

In the CWAM method, phase shift induced in the roundtrip of an intensity-modulated periodic signal is used to calculate the range (R).

$$\Delta\Phi = k_M d = \frac{2f_M}{c}2R, \qquad R = \frac{c\Delta\Phi}{4f_M},$$

where c is the speed of light in vacuum, k_M is the wavenumber associated with the modulation frequency f_M, d is the total distance traveled and $\Delta\Phi$ is the phase shift between the emitted and reflected signal.

c. Continuous Wave Frequency Modulated (CWFM)

In CWFM Lidar sensors, the reflected signal from a stationary target is mixed with the emitted signal at the photodiode in heterodyning technique producing a constant beat frequency (f_r) as shown in Fig. 6. The beat frequency is used for range calculation as

$$f_r = slope.\Delta t = \frac{B}{T}.t_{oF} = \frac{B}{T}\frac{2R}{c}\ , \Rightarrow\ R = \frac{f_r cT}{2B}$$

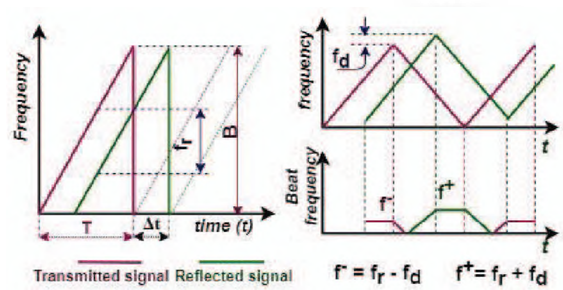

Fig. 6. : Time-frequency graph for ramp and triangular signals [14].

where B is the bandwidth, T is the time period of the ramp and Δt is equal to the time of flight (t_{oF}).

In the case of triangular frequency modulation method as shown in Fig. 6, the beat frequency for a triangular modulating signal of frequency f_m and time period T is given by [14]:

$$f_r = 4.R.B.\frac{f_m}{c}.$$

If the target is moving then beat frequency depends on the range (R) as well as the relative velocity of the moving object with respect to the sensor (v_r). The velocity considerations can be taken into account by doppler frequency (f_d) which affects the sweep of the beat frequency. In this case, range(R) and relative velocity(v_r) can be calculated as:

$$R = \frac{cT}{4B}(f^{+} + f^{-}) \ ,$$

$$v_r = \frac{\lambda}{2} f_d = \frac{\lambda}{4}(f^{+} - f^{-})$$

LiDAR sensors give 2D/3D images and development of 4D Lidar sensors (4D Lidar-on-chip by Aeva) are also in progress to obtain a clear picture of surrounding objects along with their movements. Based on the dimensions Lidar sensors can also be classified as shown in Fig. 7. Key performance parameters of the LiDARs are tabulated in table III.

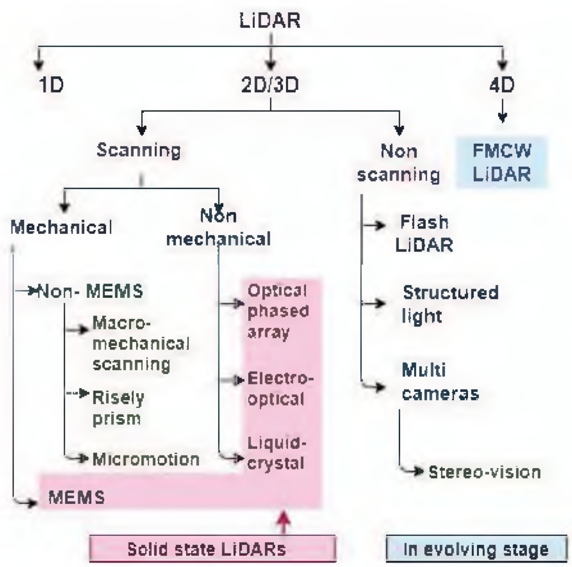

Fig. 7. Classification of LiDARs based on dimensions [15].

TABLE III KEY PERFORMANCE PARAMETERS OF THE LiDARS [16][17].

Nominal range of sensing parameters	Nominal sensor operating frequency	Interfacing	Sensor output data format
Range: 8-1000 m	-	Ethernet,USB, CAN,RS232	Digital

D. RADAR

Radars use radio frequency (RF) waves to measure the range, velocity, and angle of objects in front of it. As mentioned in the introduction, there are mainly two types of Radars based on their working principle, namely, Pulsed Radars and FMCW Radars [18][19].

a. Pulsed Radar:

Pulse radar measures range (r) based on the time delay (Δt) between the transmitted pulse and the received echo.

$$r = c * \Delta t/2 \ ,$$

where c is the speed of light in vacuum.

b. FMCW Radars:

mmWave Radars are of FMCW Radars class operating in the spectrum band between 30 GHz to 300 GHz. These Radars used in autonomous systems are mainly classified as short-range, medium-range and long-range Radars based on their range capability [20][21].

Compared to conventional pulsed Radars, FMCW Radars transmit a FMCW signal then reflected signal is mixed with the transmitted signal to generate an IF signal. By measuring the frequency and phase of this IF signal, the range, velocity, and angle of arrival of the objects in front of the Radar can be estimated.

Range (d), velocity (v), and angle (θ) of the objects are given by:

$$d = \frac{f_{if}.C}{2S},$$

Where f_{if} is the frequency of the IF signal, C is the velocity of light and S is $\frac{B}{T_C}$. B is RF bandwidth and T_C is the chirp time.

$$v = \frac{\lambda \Delta\Phi}{4\pi T_C},$$

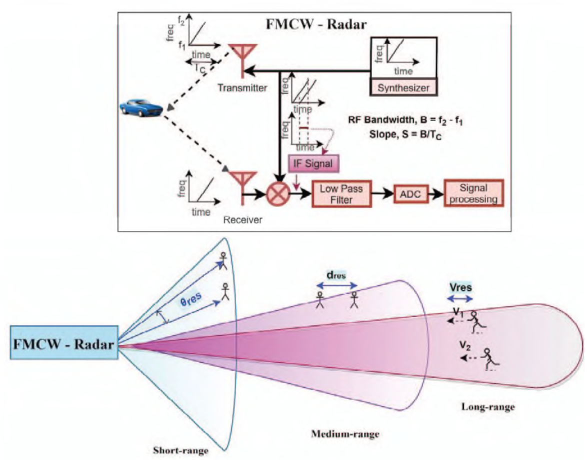

Fig. 8. mmWave Radar with key performance parameters. (up) block diagram of working principle of FMCW RADAR, (down) demonstrating the key parameters detecting (range, velocity and angle) using FMCW RADAR.

where, $\Delta\Phi$ is the phase difference between two consecutive chirps.

$$\theta = sin^{-1}(\frac{\lambda \Delta\Phi}{2\pi h}) \ ,$$

where, $\Delta\Phi$ is the phase difference between chirps of two receivers placed 'h' meters apart. Range resolution(d_{res}), velocity resolution(v_{res}), and angle resolution(θ_{res}) respectively are given by:

$$d_{res} = \frac{C}{2B},$$

$$v_{res} = \frac{\lambda}{2T_f},$$

$$\theta_{res} = \frac{\lambda}{Mh.cos(\theta)},$$

where C is the velocity of light, B is the RF Bandwidth T_f is the chirp frame time, which is NT_C. N is the number of chirps. M is the number of receivers.

As shown in Fig. 7, intuitively range, velocity and angle resolution refer to the minimum value of those parameters below which the Radar fails to measure indistinguishably

PARAMETRIC COMPARISON OF SENSORS

a. Frequency comparison

Operating frequency range of the sensors is shown in table IV and graphically shown in Fig. 9.

TABLE IV SENSORS AND FREQUENCY RANGE[10][12][22][23]

Type of sensor	Operating frequency range	Frequency range (logarithmic values)
Ultrasonic	40kHz-70 kHz	4.6-4.845
Camera (Infra Red)	300GHz-430 THz	11.48-14.63
LiDAR	200THz-600 THz	14.3-14.77
mmWave RADAR	30GHz-300 GHz	10.48-11.48

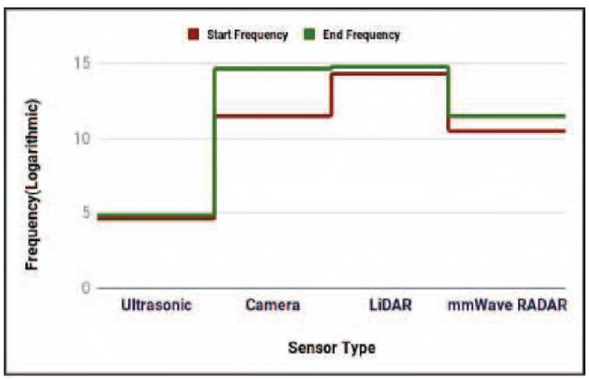

Fig. 9. Sensors vs frequency range comparison graph from Table IV.

b. Power consumption comparison

TABLE V POWER CONSUMPTION RANGE OF SENSORS COMMERCIALLY AVAILABLE [11] [12][13][16][17][23]

S.No.	Sensor type	Power consumption
1.	Ultrasonic	< 1 W
2.	Camera	0.8W-1W
3.	LiDAR	8-30 W
4.	mmWave RADAR	1-3 W (< 5 W)

Power performance of various sensors are tabulated in table V.

c. Dimensions and weight comparison

Physical dimensions and weight of various sensors are tabulated in table VI.

TABLE VI DIMENSIONS AND WEIGHT OF SENSORS COMMERCIALLY AVAILABLE [11][12][13][16][17][23]

S. No	Sensors type	Example of sensor	Weight	Dimensions in mm
1.	Ultra-sonic	Bosch, Maxbotix	14g (upto 50g)	44 (length)* 26(width) diameter:23
2.	Camera	Omron thermal sensor, Omnivision (OV10625)	SoC	14*18*8.93 (7.3*7.8)
3.	LiDAR	Velodyne,Ouster (OS0,OS1, OS2)	400g-1 kg	Diameter: 19.6 height: 98.5
4.	mmWave RADAR	TI (AWR1843)	SoC	10.4*10.4

III. Processing platforms for autonomous systems

For processing the data obtained from these various available sensors, different processing platforms are used. As mentioned in the previous section, hardware platforms are mainly classified into three categories, which are MCU based, MPU based and FPGA based.

First and foremost important aspect to be considered is hardware interfacing compatibility. For example, if the sensor har I2C (e.g. D6T-32L-01A thermal sensor) interfacing then the hardware platform needs to have I2C functionality to be able to interface with it. The other main important aspects include portability, power consumption, computational resources, software compatibility of these platforms.

IV. Machine learning for autonomous systems

As mentioned in the previous sections, multiple sensors are essential to meet the growing challenges of autonomous systems in terms of reliability, speed, accuracy and safety. So sensor fusion is employed to fuse the data from cameras (including thermal and IR), LiDARs and RADARs in addition to ultrasound sensors, localization sensors such as GPS and IMU sensors.

Some of the well-known and popular multi sensor data/image fusion techniques are intensity-hue-saturation (IHS), high-pass filtering, principal component analysis

(PCA), different arithmetic combination methods such as Brovey transform, multi-resolution analysis-based methods such as pyramid algorithm and wavelet transform, and Artificial Neural Networks (ANNs) [24]. Details of these methods, merits and demerits associated with these methods can be found in [24].

Latest trend in achieving high dimensional multi sensor data fusion is using ANNs with raw data without pre-processing [25]. As shown in Figure, fusing global and local features extracted from multiple sensors using deep auto-encoder network and deep convolutional layer network respectively to form a final output image will be highly reliable for navigation of autonomous vehicles in adverse weather conditions too.

Extraction of local features will be achieved by convolutional neural networks (CNNs) and these have been proven to be effective for local-level feature extraction of dynamic/video data already. This network will be composed of several layers of convolution and pooling to extract low-dimensional (local) features in hierarchical manner [25][26].

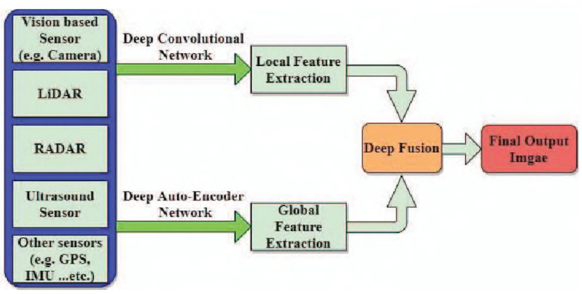

Fig. 10. Sensor fusion for autonomous systems.

Conclusion

We presented the state of the art of the key sensors such as vision based sensors, thermal cameras, LiDARs and RADARs used in autonomous systems. Their key performance parameters such as operating frequency, range, velocity, angle of arrival, field of view, interfacing with hardware platforms, computing platforms and sensors data output format were discussed. Latest trends in machine learning aspects for reliable imaging, sensor fusion were also discussed. With this information, the potential applications and the conditions where the requirement of different sensors can be estimated.

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