PDHonline Course M545 (8 PDH)

Machine Vision (MV)

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LIST OF ABBREVIATIONS

A

ADC—AD Converters

AIA—Automated Imaging Association

B

BCC- Blind Carbon Copy

BGA—Ball Grid Array

C

PCAGR—Compound Annual Growth Rate

CCG—Charge-Coupled Device

CCTV—Closed Circuit Television

CEU—Continuing Education Units

CFA—Color Filter Array

COG—Center of Gravity

D

DPI—Dots Per Inch

DMP—Directly Marketed Part

E

ECC—Error Checking and Correction

G

GIF—Graphic Interchange Format

GUI—Graphical User Interface

I

IEEE—Institute of Electrical and Electronic Engineers

I/O—Input / Output

ISA—Internet Security and Acceleration

J

JPEG—Joint Photographic Experts Group

L

LED—Light Emitting Diode

M

MTF—Modulation Transfer Function

MG--Megabytes

MHz--Megahertz

MTF—Modular Transfer Function

MV—Machine Vision

O

OCR—Optical Character Recognition

P

PC—Personal Computer

PCB—Printed Circuit Board

PCI—Peripheral Component Interconnect

PDA—Portable Digital Assistant

PCT—Portable Data Collection Terminal

PNG—Portable Network Graphics

PPI—Pixels Per Inch

PWM—Pulse Width Modulation

PPM—Parts Per Million

R

RFID—Radio Frequency Identification

RFQ—Request for Quote

RGB—Red/Green/Black

S

SOW—Statement of Work

SVGA—Super Video Graphics Array

T

TIFF—Tag Image File Format

U

USB—Universal Serial Bus

V

VGA—Video Graphic Array

VME—Virtual Memory Extension

LIST OF FIGURES

APPROACH TO THIS COURSE:

If you have taken any of my courses before you know that they are written at the university level and are for the most part technical in nature. This course is no different. If I may, let me recommend to you the following approach to successfully navigating the material and taking the quiz when completed:

- Print the quiz necessary for completion and certification so that CEUs may be obtained.
- As you read the course material, refer to the quiz to be aware of the questions being asked.
- Answer the questions as you progress through the course. (In some cases, the questions are not in chronological order relative to the course material itself.)
- Take the course using: PQRST
    - Preview--Skim the text reading each heading and the first sentence of each paragraph
    - Question—Take a look at the quiz you have printed off so that when you read, you will be looking for specific information
    - Read—Read the text. Please don't speed read.
    - Summarize—Have you some idea as to answers? Has the text adequately covered all of the questions in the quiz?
    - Test—Take the quiz using the notes gained from reading the material.
- Please read the glossary of terms prior to beginning the actual course. If you are new to machine vision, this will aid your efforts in completion. It will only take a few minutes to review the glossary and will save you considerable time during your read.

Now, please use my recommendations above as you see fit. You did not get where you are without developing methodology for studying. Hope you enjoy this one.

MACHINE VISION (MV)

INTRODUCTION

Machine vision is a rapidly evolving technology used to replace or complement manual inspections, physical measurements, ensuring safety, and facial recognition. The technology uses digital cameras and image processing software in a variety of different industries to automate production, increase production speed and yield, and to improve product quality. One primary objective is determining the quality of a product through inspection when high-speed production is required. This industry is knowledge-driven and experiences an ever- increasing complexity of components, hardware modules, and software programs that define machine vision systems. In the last few years, sales markets pertaining to machine vision components and systems have grown significantly. We will address the growth of the MV industry in the text to follow. We will look at domestic and global growth and projections for future growth of the technology

Machine vision, also known as "industrial vision" or "vision systems", is primarily focused on computer vision relative to industrial manufacturing processes like defect detection. Non-manufacturing processes such as traffic control and healthcare have also enjoyed significant and important growth in the past decade. Inspection processes are generated by responsive input needed for control; for example, robotic control and/or default verification. The primary system consists of cameras capturing, interpreting and signaling individual control systems related to some pre-determined tolerance or requirement. These requirements are written into software within the cameras themselves; i.e., “smart cameras”, or residing in PCs located in remote locations. These systems have increasingly become more powerful while at the same time easy to use. Recent advancements in machine vision technology, such as smart cameras mentioned above and embedded machine vision systems, have increased the scope of MV markets for a wider application in the industrial and non-industrial sectors.

BASIC OPERATION AND HARDWARE REQUIRED:

Let’s take a very quick look at several components and systems used when applying vision to specific applications. All applications basically need the same components and hardware but very specific individual software relative to the task at hand. Very rarely is the software generic. The first four (4) JPEGS below show applications in manufacturing processes. Those following indicate non-manufacturing uses for MV technology.

MANUFACTURING

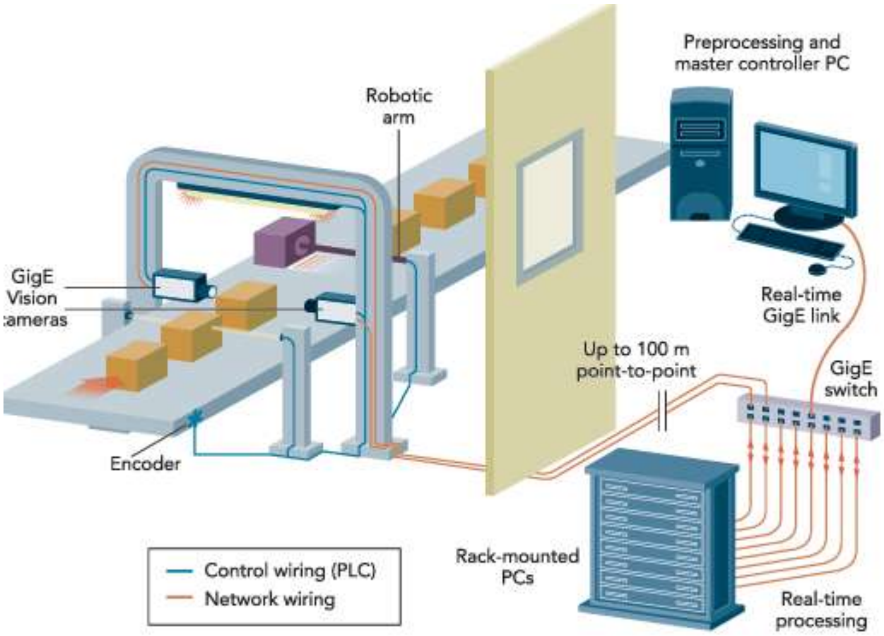

FIGURE 1: Basic Systems for Counting, Reading and Metrology

You can see from Figure 1, products advancing down a conveyor past cameras mounted on either side of that line. These cameras are receiving images and processing information relative to specifications pre-loaded into operating software which drives the system. The number of cameras and certainly the placement of those cameras is dependent upon the information required from the system. One type of specification might be a physical dimension of the product itself. The image for each may look similar to the following given by Figure 2 below.

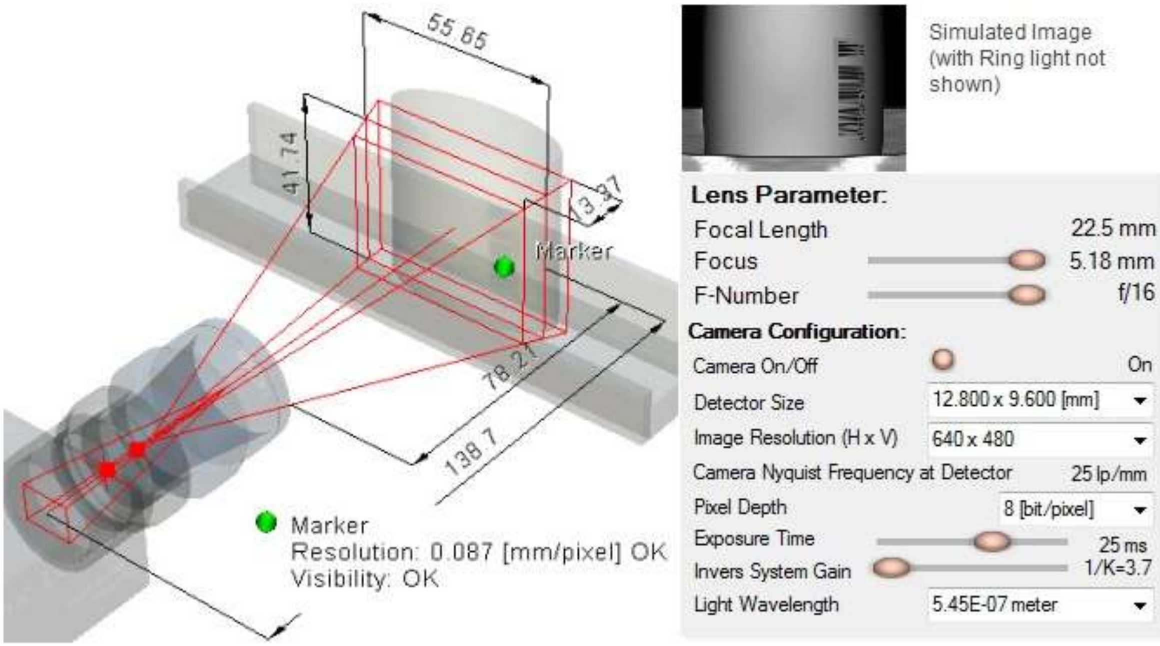

FIGURE 2: TYPICAL INSPECTION PROCESS OF COMPONENT

In this example, 55.65 mm, 41.74 mm, and 13.37 mm are being investigated and represent the critical-to-quality information. The computer program will have the "limits of acceptability"; i.e., maximum and minimum data used as baseline information from which comparisons will be made. Dimensions falling outside these limits will not be accepted. The product will be removed from the conveyor for disposition; i.e., either repair or disposal. Generally, a robotic arm removes or pushes the "off-quality" product to a holding area where the out-of-tolerance dimension or dimensions may be investigated later.

Another usage for machine vision is simple counting and/or barcode reading. Figures 3 and 4 are actual cameras mounted on assembly lines in manufacturing operations. Figure 3 is a counting operation and Figure 4 is barcode reading.

FIGURE 3: SYSTEM USED FOR COUNTING COMPONENTS

FIGURE 4: SYSTEM FOR BARCODE READING

<u>NON-MANUFACTURING USES FOR MACHINE VISION:</u>

FACIAL RECOGNITION:

One example of a non-industrial application for machine vision is facial recognition. This technology is generally considered to be one facet of the biometrics technology suite. Facial recognition is playing a major role in identifying and apprehending suspected criminals as well as individuals in the process of committing a crime or unwanted activity. Casinos in Las Vegas are using facial recognition to spot "players" with shady records or even employees complicit with individuals trying to get even with "the house". In addition, we are seeing more and more facial recognition systems in airports supporting TSA inspection. Another use is facial recognition used in cell phones as biometric login. This technology incorporates visible and infrared modalities face detection, image quality analysis, verification and identification. Many companies use cloud-based image-matching technology applied to their product range. This provides the ability to apply theory and innovation to challenging problems in the real world. Facial recognition technology is extremely complex and depends upon many data points relative to the human face.

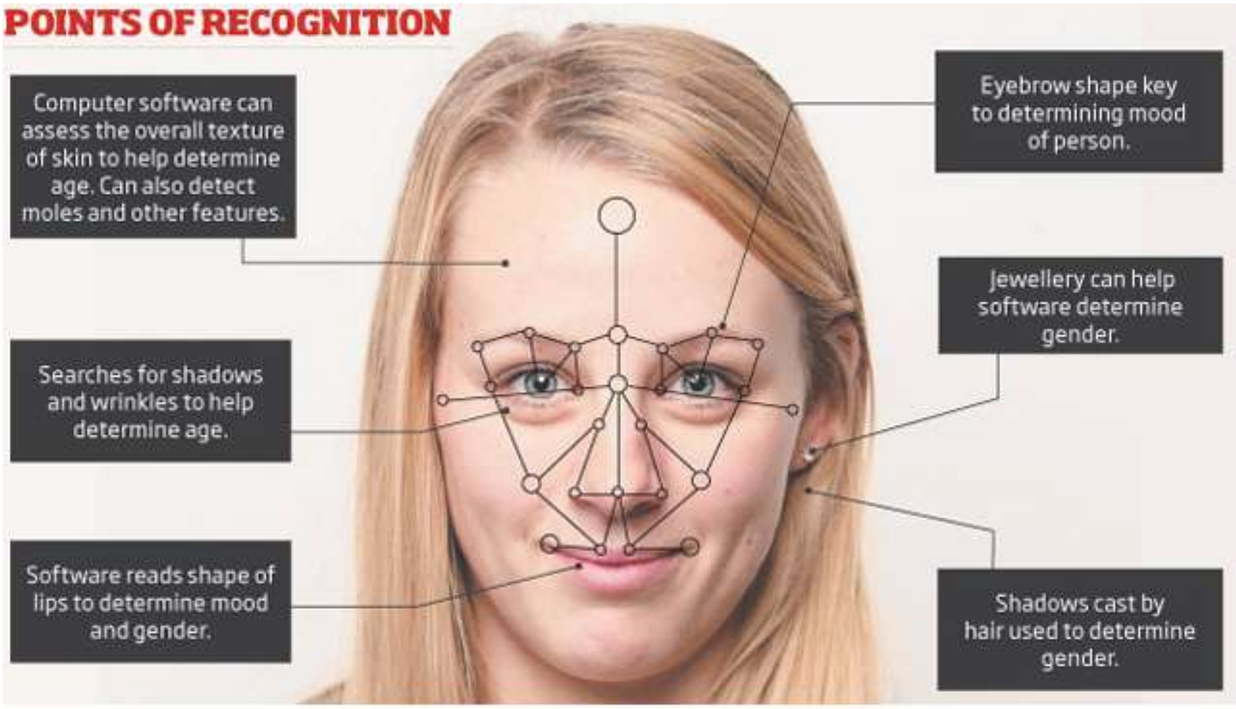

FIGURE 5: POINTS OF RECOGNITION FOR FACIAL RECOGNITION

Facial recognition has a very specific methodology associated with it. Basic points of recognition are given as shown in Figure 5 above. You will notice the more prominent features are considered first: i.e.

- Eyes and eyebrows
- Nose
- Forehead
- Mouth
- Ears
- The presence or absence of tattoos and/or piercings

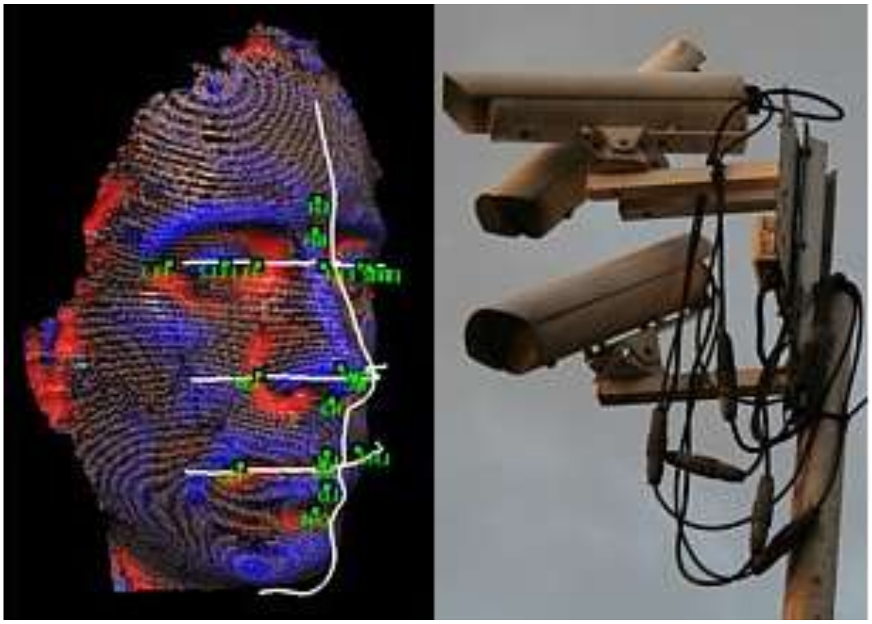

FIGURE 6: RECOGNITION FACIAL MAPPING

A grid is constructed of "surface features"; those features are then compared with photographs located in data bases or archives. In this fashion, positive identification can be accomplished.

One of the most successful cases for the use of facial recognition was the April 15, 2013 bombing during the Boston Marathon. Cameras mounted at various locations around the site of the bombing captured photographs of Tamerian and Dzhokhar Tsarnaev prior to their backpacks being positioned for both blasts. Even though this is not an example of facial recognition in the truest since of the word, there is no doubt the cameras were instrumental in identifying both criminal suspects.

Tamerlan (front) and Dzhokhar Tsarnaev as seen on security camera footage just prior to the bombing. This and other images released by the FBI taken from other security footage and photos from bystanders would later be considered a "turning point" in the investigation, leading to the subsequent manhunt and capture.[64]

FIGURE 7: DATA USED IN BOSTON BOMBING

<u>LAW INFORCEMENT AND TRAFFIC CONTROL:</u>

Remember that last ticket you got for speeding? Maybe, just maybe, that ticket came to you through the mail with a very "neat" picture of your license plate AND the speed at which you were traveling. Probably, there was a warning sign as follows:

FIGURE 8: ENFORCEMENT ZONE

OK, so you did not see it. Cameras such as the one below were mounted on the shoulder of the road and snapped a very telling photograph.

FIGURE 9: TRAFFIC CONTROL CAMERAS

You were nailed.

DOMESTIC SECURITY:

Domestic securing is an ever-increasing need for individual homes, apartment complexes and retail establishments. You cannot go into a Wal-Mart, Home Depot, Bass Pro Shop, Costco; etc. without being confronted with video cameras capturing images.

Figure 10 shows a video camera installed on a brick structure.

FIGURE 10: VIDEO CAMERA MOUNTED ON INDIVIDUAL DWELLING

Figure 11 indicates actual video taken of shoplifting in progress.

FIGURE 11: SHOPLIFTING

One of the most interesting application involves the placement of video cameras in day care facilities. These transmissions can give interested parents a real-time look at their children while they are at work. Figure 12 depicts that possibility. Application software installed on cell phones allows access to cameras located in day care facilities so parents can view, in real time, the activities of their children.

FIGURE 12: DAY CARE FACILITY WITH CHILDREN BEING MONITORED REAL-TIME

There are many other uses for machine vision and this course will strive to detail each as we progress.

HISTORY OF MV TECHNOLOGY:

The very first use of machine vision was considered to be during WWII when German engineers wished to view the successful static firing of V-2 rocket engines. Roots of machine vision traced back to early image analysis of military applications of artificial intelligence. Studies in artificial intelligence began in the post- war period driven by increases in computer technology. Human thought more efficiently emulated through the use of modern digital computers (modern at the time!)

Other chronological developments are as follows:

1950's – Two-dimensional imaging for statistical pattern recognition developed: Gibson introduces optical flow based on his theory mathematical models. This was for optical flow computation on a pixel-by-pixel basis.

1060—Roberts begins studying 3D Machine Vision. Larry Roberts wrote his PhD thesis at MIT on the possibility of extracting 3D geometric information from 2D views in 1960. This led to much research in MIT's artificial intelligence lab and other research institutions looking at computer vision in the context of blocks and simple objects.

1970's – MIT's Artificial Intelligence Lab opens a "Machine Vision" course – Researchers begin tackling "real world" objects and "low-level" vision tasks (i.e., edge detection and segmentation**:** In 1978 a breakthrough was made by David Marr (at the MIT AI lab) who created a bottom-up approach to scene understanding through computer vision. This approach starts with a 2D sketch which is built upon by the computer to get a final 3D image.

1980's – Machine vision starts to take off in the world of research, with new theories and concepts emerging: Optical character recognition (OCR) systems were initially used in various industrial applications to read and verify letters, symbols, and numbers. Smart cameras were developed in the late 80's, leading to more wide-spread use and more applications.

1990's – Machine vision starts becoming more common in manufacturing environments leading to creation of machine vision industry: over 100 companies begin selling machine vision systems. LED lights for the machine vision industry are developed, and advances are made in sensor function and control architecture, furthering advancing the abilities of machine vision systems. Costs of machine vision systems begin dropping.

As you can see, during the last two decades, machine vision has been applied slowly but surely to a variety of manufacturing challenges, all with the goal of improving quality and productivity in the manufacturing process. Semiconductor and electronics manufacturers were early adopters; they currently account for about half of the machine vision applications found on the factory floor. But acceptance is growing quickly throughout the manufacturing sector, with machine vision systems now in place in food processing, pharmaceuticals, wood and paper, plastics, metal fabrication and other industries.

With progress has come some growing pains. Machine vision was first marketed as a new, must-see technology for manufacturing automation in the early 1980s, a lesser player amid the hype surrounding artificial intelligence and automated robotic assembly. The promise of a mechanical system -- hardware and software -- that would emulate the human eye was captivating in concept but created expectations that could not be immediately met. Start-ups were plagued by complex programming requirements, difficult installations, mediocre functionality and low reliability. The technology required to implement a system successfully was simply out of reach for most users.

After some lean years, the outlook is once again bright for machine vision as products have matured, functionality has increased, suppliers have become smarter and the cost and complexity of systems has come down. Ten years ago, machine vision systems cost from forty to sixty thousand dollars ($40,000 to $60,000,) while today they run in the five-to-twenty-thousand-dollar ($5,000 to $20,000) range. They also offer vastly improved performance, with much richer data at much higher speeds.

BENEFITS:

We are going to look at benefits for manufacturing and non-manufacturing at this time.

MANUFACTURING:

- The quality of the product is increased. Quality must be designed into a product, it can never be inspected into a product, but off-quality when it occurs, can be discovered even if the conveyor line is moving at a very rapid rate.

Sample testing can often be replaced by one hundred (100%) percent quality checks. An example is paper production. Every single square inch of paper produced can be reliably checked for flaws 'on the fly'. The result is a superior product. The same applies to the printing of patterns on textiles or the production of sheet metals: The manufacturer guarantees a one hundred (100%) percent perfect delivery, which is especially important if products are safety-critical.

- Machine vision can lead to significant cost reductions including less scrap.

Often, vision systems are employed in the early production stages. Defective parts are immediately removed from the manufacturing process and not finished. In many cases the removed part can be re-introduced into the production process. This saves materials. Defective parts never continue on to subsequent manufacturing stages and therefore incur no further costs. At the same time the system may become 'self-learning' in that it recognizes recurrent defects. This statistical information can be fed back into the process to systematically rectify the problem at the point where it originates, resulting in increased system productivity and availability.

Superior detection of small defects is definitely possible if proper systems are employed: i.e., camera, lighting, software and fixturing.

- Greatly increased measurement accuracy and repeatability may be accomplished. We will talk more about accuracy and repeatability later on.
- Reduction in human error when involving MV to the inspection process. Looking at components all day every day is a very tiring experience. Repetitive tasks done manually can now be accomplished by MV.
- Increase traceability and data logging of individual components and assemblies by reading bar codes, counting methods and inspection techniques. Much greater information and tighter process control.
- Reduced down-time and reduced set-up time.
- Lower capital equipment costs.
- Much better inventory control.
- Reduced floor space.

NON-MANUFACTURING:

1. **Enhanced law enforcement** leading to reduced number of traffic accidents and possible deaths. MV is also used to provide information for accident investigations.
2. **Reduction in shoplifting** and theft for retail establishments.
3. Providing the need to monitor, in real-time, activities in **day care centers, nursing homes and hospital environments.**
4. **Providing capabilities to monitor external areas** of warehouses, private storage areas, gated communities, state and federal buildings including post offices and court houses
5. Providing **facial recognition** capabilities for law enforcement. (NOTE: this capability is one form of biometric monitoring.)
6. **Dash cam systems** for law enforcement to record and quantify incident investigations.
7. **Unmanned aerial vehicles** used by the DOD and commercial concerns.
8. **Self-driving** or autonomous automobiles and vans.
9. **Visual search systems.** Visual search uses images as keywords as opposed to texts and searches for related images, websites, blogs, or any other posts. Visual Search Engine is programmed in a

manner that bridges the time gap between your search. For example, Google Lens allows the users to look for objects through the lens and get similar results as per their image search.

10. **Gesture recognition systems.** It is of no surprise that multiple algorithms exist in the computer vision field to detect human gestures and postures. They can interpret human gestures originated from any motion or state of the human body. For example, a store supervisor can carry out emotion recognition to determine if customers visiting the store are happy with the services or not.

11. **Computer-aided diagnosis.** Computer Vision also finds a wide range of applications in the healthcare sector. It can assist medical professionals in training. Doctors can interpret medical images used in techniques like X-Ray and MRI using computer vision efficiently.

THEORY OF OPERATION:

Machine vision is the process of interpreting pixels that are captured using a digital device such as a webcam or digital camera. Typically, machine vision can be broken into the following parts:

1. Image acquisition - how you get the image
2. Image conversion - converting the image into a usable format
3. Image processing - tweaking pixels
4. Statistical Analysis - understanding the image through numbers
5. Machine control - moving, rotating, etc. a hardware device based on the image

We will take a look at each element of the process as follows:

Image Acquisition-- Image Acquisition is how you get the image into your computer. While machine vision does not strictly indicate live or saved images, it is often more useful to have video-capture devices provide images for a machine vision application due to the need for real-time controlling of machines. During development or prototyping one can use saved images for processing which removes much of the difficultly of acquiring images until the final deployment stage.

For experimentation, image formats such as gif, jpeg, etc. that can be easily acquired via the web, can provide a large test bed of images surrounding a specific topic.

For real-time acquisition of images, Windows does provide a more standardized technique called "Video for Windows" or VFW. This technique allows you to create a single program that can then interface with most, if not all, video capture devices that are supported under Windows. RoboRealm supports this technique and we have successfully interfaced many video capture devices such as webcams, TV capture devices and digitizers.

Real-time acquisition of images in the Unix environment is somewhat more arcane and requires understanding of a specific device's interface. For many capture cards the device exposes its interface via a file- based handle, as much of other UNIX-based device drivers. However, the specific commands used to set capture images require programming code usually not transferable to different devices. Nevertheless, many machine vision applications are custom built for a specific purpose or purposes and therefore do not need to inter-operable between a large number of devices.

The result of the image acquisition process is to have in memory or on disk a sequence of bytes that represents the image in some format.

Image Conversion-- The image conversion process takes the results of the image acquisition and converts the image into a format that is easier to use during the next couple of machine vision phases. The conversion process focuses on how the image is formatted (i.e., is it a compressed image file like GIF or JPEG) and how the pixel values are stored or packed (i.e., what are the color value ranges, is the color value an integer or floating-point number?).

Many hundreds of image formats exist but some are more popular and in wider use than others. For web related applications the typical image formats of GIF, JPEG or PNG comprise the majority of the image accessible on the web. For other machine vision applications, TIFF or PPM are more widely used. If your image acquisition process leaves you with an encoded or compressed file you will need to decode the file in order to gain access to the raw pixel color values before proceeding to the next machine vision phase.

If you have chosen to skip the image acquisition phase you will most likely be dealing with images that are encoded as JPEG. To access the raw pixel values, you will need a package such as Free Image to load and provide the pixel values to your application. Note that Windows also has built-in JPEG decoding routines but Free Image supports more formats and works in multiple environments.

Traditionally, image acquisition devices will provide you with a sequence of bytes that are packed in a specific way. If you're lucky you will have a sequence of bytes that are stored as 0-255 values in sets of 3. The first byte will traditionally be the red value, followed by the blue and then green. The fourth byte will then be the next pixel's red value, and so on. This is known as an eight (8)- bit RGB packed pixel. The eight (8)- bit refers to how many bits are allocated for each component of the pixel. This format is also referred to as RGB twenty-four (24), the twenty-four (24) being the sum of 8+8+8 which represents the 3 values that comprise the pixel. This format is usually the easiest from a conceptual point of view to process and thus is usually the desired format at the end of the image conversion process.

There are many other pixel packing formats such as fourteen hundred and twenty (I420) or RGB five hundred and fifty-five (555), etc. All of the formats represent the image pixel values in a different way. For example, RGB 555 uses five (5) bits (instead of the previously mentioned 8) to store color values in an RGB sequence. The main difference is that the RGB 555 format is less precise than the RGB 24 format since fewer bits are used. The benefit is that an image is much smaller and can be transmitted much faster through smaller bandwidth pipes (note that RGB twenty-four (24) is three (3) bytes per image whereas RGB 555 is 2 bytes with one bit being unused). In addition, the loss of image color while perceptible is not significant and will usually not alter machine vision processing results. If image size and transmission is not an issue, RGB 24 is normally preferred since it is easier to work with byte aligned (- bit values) rather than have to split bytes into bits to extract the RGB triplet.

Image Processing and Analysis-- Once you have the image in a usable format (RGB 24 is in use in RoboRealm) you can start the image processing phase of the machine vision application. Image processing is perhaps the most time consuming and difficult phase of a machine vision application. This stage requires you to convert the image using any number of many techniques to change the image into a desired view.

For example, if you have a need to track an object then you first need to decide what characteristic about that object can be used to detect the object as robustly as possible. These characteristics are often referred to as image featured. Note that more than one feature and sometimes thousands can be used to detect or track objects. These features can range from simple color or intensity (object brightness) to more complex features such as edges or shapes. Some features to use when determining your approach can be

- Color - does the object have a unique color (i.e., neon green, bright purple, etc.)
- Intensity - is the object brighter or darker than other objects in the image
- Object location - is the object always in the top of image, right corner of image, etc.
- Movement - does the object move in a specific way, i.e., does it wiggle, sway, move slowly, stationary
- Texture/pattern - does the object have a unique texture (i.e., tree bark, red bricks, pebble stones)
- Edges - does the object have well-defined edges that are straight or circular
- Structure - given simpler blobs or parts of the image can the object be composed of simpler objects arranged in a specific manner

Obviously, many features can be extracted from an image. Most of image processing is about using the right features out of the millions that can be extracted. Sometimes this process can be automated, but given limited time and resources a human decision on which features to use can help considerably.

Statistical Analysis-- The statistical analysis term is widely used over a variety of technology disciplines, and has varying meanings. To define image analysis within machine vision, we first consider the broad scope of the typical industrial inspection or guidance application. Digital cameras or other complex sensors are integrated with lenses or specialized optics along with dedicated light sources to capture a picture or representation of an object. By various means, the picture might be manipulated to enhance and optimize the content. Specialized software tools are used to extract information from features in the picture. Ultimately, that information is provided to the automated process for tasks like guidance, measurement, or quality assurance.

These important steps within a successful machine vision application can be grouped into general operational categories. The terms image acquisition, image processing, image analysis, and results processing often are used to describe the four actions mentioned above. (Although the terminology certainly makes sense for machine vision, bear in mind that these designations are only loosely used, and can take on different meanings depending on context.) In this tutorial we will focus on image analysis, and will cover just a few of the very basic concepts of this broad and important part of machine vision technology and software.

For our purposes then, image analysis is the part of machine vision where the bulk of the actual "work" takes place. In short, image analysis is where data and information required by the application and the automation system are extracted from an image. Getting the right information, repeatability and reliably, requires competent specification and application of one or perhaps many inspection algorithms. To help with that, one should first understand a couple of the ways content is extracted from an image.

Machine Control--Once the appropriate numbers have been calculated, they need to be translated into motor or servo movements in order for the robot or machine to react to what it sees. Controlling a machine from a PC computer typically requires a board that translates serial or parallel commands into PWM (Pulse Width Modulation) or actual electrical current via an H-bridge. Many servo boards meant to control traditional servos exist. Have a look at Parallax for examples of such boards. Sending commands to such a board requires that the statistical numbers calculated from an image-processed image be translated into left and right motor commands in the case of steering a robot. This translation can be in the form of simple condition statements that turn a motor on or off based on some threshold value. For example, if the COG (Center of Gravity) of an image is left of the image center, send the servo board a 255 for the left motor. Likewise send a two hundred and fifty-five (255) position command to the servo controller board for the right servo to move the robot right.

Often, controlling several motors based on an image may require inverse kinematics to determine the angular values for each of the servos required to position an arm or other complex robotic device to its desired position. For example, if a robotic arm has two servos that function like a human arm to position the hand at a certain point requires the two servos to have specific angles that will position the hand at a certain X, Y point. Calculating angular values for these servos is dependent on the resulting X, Y coordinate and on the length of the arm parts involved.

Filtering-- Image filtering allows you to apply various effects on photos. The type of image filtering described here uses a 2D filter similar to the one included in Paint Shop Pro as User Defined Filter and in Photoshop as Custom Filter.

Thresholding-- The simplest property that pixels in a region can share is intensity. So, a natural way to segment such regions is through *thresholding*, or the separation of light and dark regions. Thresholding creates binary images from grey-level images by turning all pixels below some threshold to zero and all pixels above that threshold to one. What you want to do with pixels at the threshold doesn't matter, as long as you're consistent.

The major problem with thresholding is that we consider only the intensity, not any relationships between the pixels. There is no guarantee that the pixels identified by the thresholding process are contiguous. We can easily include extraneous pixels that aren't part of the desired region, and we can just as easily miss isolated pixels within the region, especially near the boundaries of the region. These effects get worse as the noise gets worse, simply because it's more likely that a pixel's intensity doesn't represent the normal intensity in the region. When we use thresholding techniques, we typically have to play with it, sometimes losing too much of the region and sometimes getting too many extraneous background pixels. (Shadows of objects in the image are also a real pain—not just where they fall across another object but where they mistakenly get included as part of a dark object on a light background.)

One extremely simple way to find a suitable threshold is to find each of the modes (local maxima) and then find the valley (minimum) between them. While this method appears simple, there are two main problems with it:

1. The histogram may be noisy, thus causing many local minima and maxima. To get around this, the histogram is usually smoothed before trying to find separate modes.

2. The sum of two separate distributions, each with their own mode, may not produce a distribution with two distinct modes.

Several factors affect the suitability of the histogram for guiding the choice of the threshold: the separation between peaks;

- the noise content in the image;
- the relative size of objects and background;
- the uniformity of the illumination;
- The uniformity of the reflectance.

Pixel Counting-- A pixel is generally thought of as the smallest single component of a digital image. However, the definition is highly context-sensitive. For example, there can be "printed pixels" in a page, or pixels carried by electronic signals, or represented by digital values, or pixels on a display device or pixels in a digital camera (photosensor elements). This list is not exhaustive and, depending on context, synonyms include pel, sample, byte, bit, dot, and spot. *Pixels* can be used as a unit of measure such as: 2400 pixels per inch, 640 pixels per line, or spaced ten (10) pixels apart.

The measures dots per inch (dpi) and pixels per inch (ppi) are sometimes used interchangeably, but have distinct meanings, especially for printer devices, where dpi is a measure of the printer's density of dot (e.g. ink droplet) placement. For example, a high-quality photographic image may be printed with six hundred (600) ppi on a twelve hundred (1200) dpi inkjet printer. Even higher dpi numbers, such as the forty-eight hundred (4800) dpi quoted by printer manufacturers since 2002, do not mean much in terms of achievable resolution.

The more pixels used to represent an image, the closer the result can resemble the original. The number of pixels in an image is sometimes called the resolution, though resolution has a more specific definition. Pixel counts can be expressed as a single number, as in a "three-megapixel" digital camera, which has a nominal three million pixels, or as a pair of numbers, as in a "640 by 480 display", which has six hundred and forty (640) pixels from side to side and four hundred and eighty (480) from top to bottom (as in a VGA display), and therefore has a total number of 640×480 = 307,200 pixels or 0.3 megapixels.

The pixels, or color samples, that form a digitized image (such as a JPEG file used on a web page) may or may not be in one-to-one correspondence with screen pixels, depending on how a computer displays an image. In computing, an image composed of pixels is known as a bitmapped image or a *raster image*. The word *raster* originates from scanning patterns, and has been widely used to describe similar halftone printing and storage techniques.

Segmentation--The division of an image into meaningful structures, *image segmentation*, is often an essential step in image analysis, object representation, visualization, and many other image processing tasks. In chapter 8, we focused on how to analyze and represent an object, but we assumed the group of pixels that identified that object was known beforehand. In this chapter, we will focus on methods that find the particular pixels that make up an object. A great variety of segmentation methods has been proposed in the past decades, and some categorization is necessary to present the methods properly here. A disjunctive categorization does not seem to be possible though, because even two very different segmentation approaches may share properties that defy singular categorization. The categorization presented in this chapter is therefore rather a categorization regarding the *emphasis* of an approach than a strict division.

Edge Detection-- An edge in an image is a boundary or contour at which a significant change occurs in some physical aspect of an image, such as the surface reflectance, illumination or the distances of the visible surfaces from the viewer. Changes in physical aspects manifest themselves in a variety of ways, including changes in intensity, color, and texture.

Detecting edges is very useful in a number of contexts. For example, in a typical image understanding task such as object identification, an essential step is to segment an image into different regions corresponded to different objects in the scene. Edge detection is the first step in image segmentation.

Another example is in the development of a low-bit rate image coding system in which we can code only edges. It is well known that an image that consists of only edges is highly intelligible. The significance of a physical change in an image depends on the application. An intensity change that would be classified as an edge in some application might not be considered an edge in other application.

In object identification system, an object's boundaries may be sufficient for identify and contours. These represent additional details within the object and may not be considered edges. An edge cannot be defined outside. It is common for a single image to contain edges having widely different sharpnesses and scales, from blurry and gradual to crisp and abrupt. Edge scale information is often useful as an aid toward image understanding. For instance, edges at low resolution tend to indicate gross shapes, whereas texture tends to become important at higher resolutions. An edge detected over a wide range of scale is more likely to be physically significant in the scene than an edge found only within a narrow range of scale. Furthermore, the effects of noise are usually most deleterious at the finer scales of the context of an application.

Color Analysis— A camera system's response to color varies not only between different makes and models for its components but also between components of the same make and model. Scene illumination adds further uncertainty by altering a color's appearance. These subtleties come about from the fact that light emanates with its own color spectrum. Each object in a scene absorbs and reflects (filters) this spectrum differently and the camera system responds to (accepts and rejects) the reflected spectrum in its own way. The challenge for color machine vision is to deliver consistent analysis throughout a system's operation and between systems performing the same task while also imitating a human's ability to discern and interpret colors.

The majority of today's machine vision systems successfully restrict themselves to grayscale image analysis. In certain instances, however, it is unreliable or even impossible to just depend on intensity and/or geometric (shape) information. In these cases, the flexibility of color machine vision software is needed to:

- Optimally convert an image from color to monochrome for proper analysis using grayscale machine vision software tools.
- Calculate the color difference to identify anomalies.
- Compare the color within a region in an image against color samples to assess if an acceptable match exists or to determine the best match.
- Segment an image based on color to separate object or features from one another and from the background.

COLOR ANALYSIS TOOLS

Currently there are software tools available to help identify parts, products and items using color, assess quality from color and isolate features using color. A color matching tool determines the best matching color from a collection of samples for each region of interest within an image. A color sample can be specified either interactively from an image—with the ability to mask out undesired colors—or using numerical values.

A color sample can be a single color or a distribution of colors (histogram). The color matching method and the interpretation of color differences can be manually adjusted to suit particular application requirements. The color matching tool also can match each image pixel to color samples to segment the image into appropriate elements for further analysis using other tools. The color distance tool reveals the extent of color differences within and between images, while the projection tool enhances color to grayscale image conversion for analysis—again using other tools.

The majority of color cameras feature a single sensor that employs a color filter array (CFA) or mosaic. This mosaic typically consists of red (R), green (G) and blue (B) optical filters overlaid in a specific pattern over the pixels.

A demo-saicing operation— performed either by the camera or software—is needed to convert the raw sensor data into a proper color image, for example, with an RGB value for each pixel position. Several demo-saicing techniques exist, each with a trade-off between speed and quality, such as an introduction of color artifacts. This demo-saicing operation can and must be adjusted to normalize the (RGB) response of the setup; for example, camera system and illumination, and thus produce consistent color images.

The normalization factors are determined—most often automatically—by performing a white balance calibration: the machine vision system is presented a sample deemed white and the normalization factors to produce a white image are computed accordingly.

Controlled scene illumination also is critical for effective color machine vision—the light source, usually white and diffused, must provide a sufficiently consistent output and the scene must be adequately shrouded from the effects of varying ambient light.

Many color-verification systems match the color contained within images to a predefined color. Determining the extent of color control needed in the system depends upon the application and how the tools are applied. If a part simply needs to be verified as red and the system need not analyze the exact color composition, strict controls may not be needed. However, if a machine-vision system needs to ascertain that the red exactly matches a defined pantone color, the system may benefit from white-balancing and color calibration. Special attention should also be given to control even minor color shifts that are the result of aging lights, temperature, and ambient lighting conditions.

When designing a color vision system, the wavelengths contained in the light source, those reflected and absorbed by the surface of the part, and the frequency-response curve of the camera must be considered. Like the eye, a camera gathers light reflected (or transmitted) from objects. If light strikes a shiny surface and reflects into the camera, surface color information is lost. For this reason, color vision systems will often benefit from using diffuse or disparate light sources such as ring lights. Fortunately, several companies provide products that improve the robustness of color systems. Most often, color machine-vision systems should use cameras that provide automatic white balancing, and lights that provide a uniform distribution of intensity over the color spectrum.

Like monochrome systems, color machine-vision systems operate effectively if they can easily detect the differences between good and bad parts. Choosing the correct color space is an important aspect of the system design, as it will enhance the separation distance applied to the colors. Pure white light is comprised of a spectrum of colored wavelengths of equal intensity. A typical 24-bit color camera separates images into individual red, blue, and green planes, each with 8 bits of depth using color filters. By mixing different R, G, and B values, nearly all visible colors can be created (see Fig. 1). This recombination is a result of the additive properties of primary colors.

Neural Net Discovery-- In machine learning, artificial neural networks (ANNs) are a family of statistical learning algorithms inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which can compute values from inputs, and are capable of machine learning as well as pattern recognition, thanks to their adaptive nature.

For example, a neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated. This determines which character was read.

Like other machine learning methods - systems that learn from data - neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, including computer vision and speech recognition**.**

Pattern Recognition--Although pattern recognition and image processing have developed as two separate disciplines, they are very closely related. The area of image processing consists not only of coding, filtering, enhancement, and restoration, but also analysis and recognition of images. On the other hand, the area of pattern recognition includes not only feature extraction and classification, but also preprocessing and description of patterns. It is true that image processing appears to consider only two-dimensional pictorial patterns and pattern recognition deals with one-dimensional, two-dimensional, and three-dimensional patterns in general. However, in many cases, information about one-dimensional and three-dimensional patterns is easily expressed as two-dimensional pictures, so that they are actually treated as pictorial patterns. Furthermore, many of the basic techniques used for pattern recognition and image processing are very similar in nature. Differences between the two disciplines do exist, but we also see an increasing overlap in interest and a sharing of methodologies between them in the future.

SYSTEM REQUIREMENTS:

Typically, a machine vision system is PC-based, using a group of devices to receive, analyze and interpret the image of a real scene. The system makes judgments on the image using predefined criteria set by the user. This information can be used to automate go/no-go inspection decisions, assembly verification, part location and machine guidance, gauging/dimensional measurements, feedback control loops and a host of other tasks. It is a common misperception that machine vision systems provide generic optical detection and processing capabilities. While every system includes essential functions, most customers require some level of customization in development and should be cautious of vendors claiming to have "one-size-fits-all" solutions. Systems perform best in their own tightly controlled, highly specialized environment.

Application requirements vary drastically by industry, but a number of components are common to every machine vision system. Technology is evolving rapidly in all these areas, creating new opportunities on the manufacturing floor. The following are common components:

Cameras – CCD (Charged-Coupled Device) cameras are becoming smaller, lighter and less expensive. Images are sharper and more accurate, and the new dual output cameras produce images twice as fast as previous models. A new generation of CCD color cameras adds another dimension to machine vision by enabling systems to better detect and discriminate between objects, remove backgrounds and perform spectral analysis. As we will see later in this course, adding color can make a significant difference relative to inspections and allows a much greater flexibility. Camera configurations vary considerably. The following graphics will indicate what cameras look like and give you some idea as to size and basic configuration.

FIGUR 13: COGNEX SMART CAMERA

FIGURE 14: MANTA SMART CAMERA

FIGURE 15: GIGE FIREWIRE

FIGURE 16: TELEDYNE SMART CAMERA

Frame grabbers -- These specialized A/D converters (Analog to digital) change video or still images into digital information. Most frame grabbers are printed circuit boards compatible with the most common types of bus structures, including peripheral component interconnect (PCI), PC-104, ISA (Internet Security and Acceleration), VME (Virtual Memory and Extension) and Compact PCI. Today's frame grabbers offer greater stability and accuracy than earlier models, and some can even handle image processing and enhancement on the fly, using digital signal processing techniques. A graphic showing how this works is given as follows:

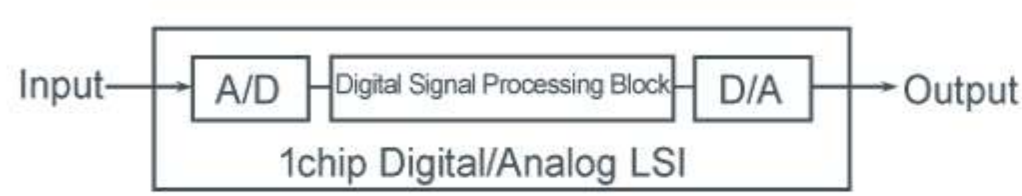

FIGURE 17: A/D CONVERTERS

PCs -- With the advent of the PCI bus, the PC has had a major impact on the use of machine vision in manufacturing applications. Personal computers previously could not gather data at a rate fast enough to keep up with machine vision's heavy I/O requirements, including data transfer rates of twenty (20) MB/second or greater. The VME bus, a specialized architecture for data acquisition and process control, with bus speeds of forty (40) MB/second, became a development standard instead. However, today's PCs can handle machine vision's demands, with one hundred and thirty-two (132) MB/second PCI bus transfer speeds and >one hundred (100) MHz Pentium microprocessors. PCs are now routinely embedded into equipment on the factory floor. The distributed intelligence made possible by PC technology has contributed immeasurably to the pace and effectiveness of factory automation.

Software -- Graphical user interfaces (GUI) and libraries of high-level software modules operating in standard environments such as Windows have eased the development process and made machine vision a user-friendly tool. Leading-edge software suppliers have begun to provide object-oriented application development tools that will speed application development even more.

New technologies -- High-speed serial data ports like the Universal Serial Bus and Fire Wire (IEEE 1394) will speed data transfer and information throughput, increasing the overall capability of machine vision systems. USB has already been adopted as an industry standard by PC and peripheral vendors, and will make it simpler to connect digital cameras to powerful embedded PCs. However, reaching real-time video rates will require the higher-speed Fire Wire.

CRITICAL FACTORS:

As with any technology, there are certain elements critical to success. MV is no different. There are six (6) basic and critical factors for choosing an imaging system. These are as follows:

- **Resolution**--A higher resolution camera will undoubtedly help increase accuracy by yielding a clearer, more precise image for analysis. The downside to higher resolution is slower speed. The resolution of the image required for an inspection is determined by two factors: 1.) the field of view required and 2.) minimal dimension that must be resolved by the imaging system. Of course, lenses, lighting, mechanical placement and other factors come into play but, if we confine our discussion to pixels, we can avoid having to entertain these topics. This allows us to focus on the camera characteristics. Using an example, if a beverage packaging system requires verification that a case is full prior to sealing, it is necessary for the camera to image the contents from above and verify that twenty-four (24) bottle caps are present. It is understood that since the bottles and caps fit within the case, the caps are then the smallest feature within the scene that must be resolved. Once the application parameters and smallest features have been determined, the required camera resolution can be roughly defined. It is anticipated that, when the case is imaged, the bottle caps will stand out as light objects within a dark background. With the bottle caps being round, the image will appear as circles bounded by two edges with a span between the edges. The edges are defined as points where the image makes a transition from dark to light or light to dark. The span is the diametrical distance between the edges. At this point, it is necessary to define the number of pixels that will represent each of these points. In this application, it would be sufficient to allow three pixels to define each of the two edges and four pixels to define the span. Therefore, a minimum of ten pixels should be used to define the 25mm bottle cap in the image. From this, we can determine that one pixel will represent 2.5mm of the object itself. Now we can determine the overall camera resolution. Choosing 400mm of the object to represent the horizontal resolution of the camera, the camera then needs a minimum of 400/2.5 = 160 pixels of horizontal resolution. Vertically, the camera then needs 250/2.5 = 100 pixels of vertical resolution. Adding a further ten percent (10%) to each resolution to account for variations in the object location within the field of view will result in the absolute minimum camera resolution. There are pros and cons to image resolution as follows.

  Pros and cons of increasing resolution

  Digital cameras transmit image data as a series of digital numbers that represent pixel values. A camera with a resolution of two hundred by one hundred (200 x 100) pixels will have a total of twenty thousand (20,000) pixels, and, therefore, twenty thousand (20,000) digital values must be sent to the acquisition system. If the camera is operating at a data rate of twenty-five (25) MHz, it takes forty (40) nanoseconds to send each value. This results in a total time of approximately zero point zero zero zero eight (0.0008) seconds, which equates to one thousand two hundred (1,250) frames per second. Increasing the camera resolution to six-forty by four-eighty (640 x 480) results in a total of three hundred seven thousand two hundred (307,200) pixels, which is approximately fifteen (15) times greater. Using the same data rate of twenty-five (25) MHz, a total time of 0.012288 seconds, or eighty-one point four (81.4) frames per second, is achieved. These values are approximations and actual camera frame rates will be somewhat slower because we have to add exposure and setup times, but it is apparent that an increase in camera resolution will result in a proportional decrease in camera frame rate. While a variety of camera output configurations will enable increased camera resolution without a sacrifice in frame rate, these are accompanied by additional complexity and associated higher costs.

- **Speed of Exposure**—Products rapidly moving down a conveyor line will require much faster exposure speed from vision systems. Such applications might be candy or bottled products moving at extremely fast rates. When selecting a digital camera, the speed of the object being imaged must be considered as well. Objects not moving during exposure would be perfectly fine with relatively simple and inexpensive camera or cameras. These could be used and provide perfectly satisfactory results. Objects moving continuously require other considerations. For other cases, objects may be stationary only for very short periods of time, then move rapidly. If this is the case, inspection during the stationary period would be the most desirable.

  Stationary or slow-moving objects: Area array cameras are well suited to imaging objects that are stationary or slow moving. Because the entire area array must be exposed at once, any movement during the exposure time will result in a blurring of the image. Motion blurring can, however, be controlled by reducing exposure times or using strobe lights.

  Fast-moving objects: *When using an area array camera for objects in motion, some consideration must be taken for the amount of movement with respect to the exposure time of the camera. Also, object resolution, defined as the smallest feature of the object represented by one pixel, is a consideration. A rule of thumb when acquiring images of a moving object is that the exposure must occur in less time than it takes for the object to move beyond one pixel. If you are grabbing images of an object that is moving steadily at 1cm/second and the object resolution is already set at 1 pixel/mm, then the absolute maximum exposure time required is 1/10 per second. There will be some amount of blur when using the maximum amount of exposure time since the object will have moved by an amount equal to 1 pixel on the camera sensor. In this case, it is preferable to set the exposure time to something faster than the maximum, possibly 1/20 per second, to keep the object within half a pixel. If the same object moving at 1cm/second has an object resolution of 1 pixel/micrometer, then a maximum exposure of 1/10,000 of a second would be required. How fast the exposure can be set will be dependent on what is available in the camera and whether you can get enough light on the object to obtain a good image. Additional tricks of the trade can be employed when attempting to obtain short exposure times of moving objects. In cases where a very short exposure time is required from a camera that does not have this capability, an application may make use of shutters or strobed illumination. Cameras that employ multiple outputs can also be considered if an application requires speeds beyond the capabilities of a single output camera.*

Frame Rate--The frame rate of a camera is the number of complete frames a camera can send to an acquisition system within a predefined time period. This period is usually stated as a specific number of frames per second. As an example, a camera with a sensor resolution of six hundred forty by four hundred eighty (640 x 480) is specified with a maximum frame rate of fifty (50) frames per second. Therefore, the camera needs twenty (20) milliseconds to send one frame following an exposure. Some cameras are unable to take a subsequent exposure while the current exposure is being read, so they will require a fixed amount of time between exposures when no imaging takes place. Other types of cameras, however, are capable of reading one image while concurrently taking the next exposure. Therefore, the readout time and method of the camera must be considered when imaging moving objects. Further consideration must be given to the amount of time between frames when exposure may not be possible.

- **Spectral Response and Responsiveness**--All digital cameras that employ electronic sensors are sensitive to light energy. The wavelength of light energy that cameras are sensitive to typically ranges from approximately four hundred (400) nanometers to a little beyond one thousand (1000) nanometers. There may be instances in imaging when it is desirable to isolate certain wavelengths of light that emanate from an object, and where characteristics of a camera at the desired wavelength may need to be defined. A matching and selection process must be undertaken by application engineers to insure proper usage of equipment relative to the needs at hand. There may be instances in imaging when it is desirable to isolate certain wavelengths of light that emanate from an object, and where characteristics of a camera at the desired wavelength may need to be defined. Filters may be incorporated into the application to tune out the unwanted wavelengths, but it will still be necessary to know how well the camera will respond to the desired wavelength. The responsiveness of a camera defines how sensitive the camera is to a fixed amount of exposure. The responsiveness of a camera can be defined in LUX or DN/(nJ/cm^2). "LUX" is a common term among imaging engineers that is used to define the sensitivity in photometric units over the range of visible light, where DN/ (nJ/ cm^2) is a radiometric expression that does not limit the response to visible light. In general, both terms state how the camera will respond to light. The radiometric expression of x DN/ (nJ/cm^2) indicates that, for a known exposure of 1 nJ/cm^2, the camera will output pixel data of x DN (digital numbers, also known as grayscale). Gain is another feature available within some cameras that can provide various levels of responsiveness. The responsiveness of a camera should be stated at a defined gain setting. Be aware, however, that a camera may be said to have high responsiveness at a high-gain setting, but increased noise level can lead to reduced dynamic range.

- **Bit Depth**--Digital cameras produce digital data, or pixel values. Being digital, this data has a specific number of bits per pixel, known as the pixel bit depth. Each application should be considered carefully to determine whether fine or coarse steps in grayscale are necessary. Machine vision systems commonly use eight (8)-bit pixels, and going to ten (10) or twelve (12) bits instantly doubles data quantity, as another byte is required to transmit the data. This also results in decreased system speed because two bytes per pixel are used, but not all of the bits are significant. Higher bit depths can also increase the complexity of system integration since higher bit depths necessitate larger cable sizes, especially if a camera has multiple outputs. Digital cameras produce digital data, or pixel values. Being digital, this data has a specific number of bits per pixel, known as the pixel bit depth. This bit depth typically ranges from eight (8) to sixteen (16)-bits. In monochrome cameras, the bit depth defines the quantity of gray levels from dark to light, where a pixel value of 0 is %100 dark and two hundred and fifty-five (255) (for 8-bit cameras) is %100 white. Values between zero (0) and two hundred and fifty-five (255O will be shades of gray, where near zero (0) values are dark gray and near two hundred and fifty-five (255) values are almost white. Ten (10)-bit data will produce one thousand and twenty-four (1024) distinct levels of gray, while twelve (12)-bit data will produce four thousand and ninety-six (4096) levels. Each application should be considered carefully to determine whether fine or coarse steps in grayscale are necessary. Machine vision systems commonly use eight (8)-bit pixels, and going to ten (10) or twelve (12) bits instantly doubles data quantity, as another byte is required to transmit the data. This also results in decreased system speed because two bytes per pixel are used, but not all of the bits are significant. Higher bit depths can also increase the complexity of system integration since higher bit depths necessitate larger cable sizes, especially if a camera has multiple outputs.

- **Lighting**— Perhaps, no other aspect of vision system design and implementation consistently has caused more delay, cost-overruns, and general consternation than lighting. Historically, lighting often was the last aspect specified, developed, and or funded, if at all. And this approach was not entirely unwarranted, as until recently there was no real vision-specific lighting on the market, meaning lighting solutions typically consisted of standard incandescent or fluorescent consumer products, with various amounts of ambient contribution. The following lighting sources are now commonly used in machine vision:

  • Fluorescent

  • Quartz Halogen – Fiber Optics

  • LED - Light Emitting Diode • Metal Halide (Mercury)

  • Xenon

  • High Pressure Sodium

  Fluorescent, quartz-halogen, and LED are by far the most widely used lighting types in machine vision, particularly for small to medium scale inspection stations, whereas metal halide, xenon, and high-pressure sodium are more typically used in large scale applications, or in areas requiring a very bright source. Metal halide, also known as mercury, is often used in microscopy because it has many discrete wavelength peaks, which complements the use of filters for fluorescence studies. A xenon source is useful for applications requiring a very bright, strobed light.

Historically, fluorescent and quartz halogen lighting sources have been used most commonly. In recent years, LED technology has improved in stability, intensity, and cost-effectiveness; however, it is still not as cost-effective for large area lighting deployment, particularly compared with fluorescent sources. However, on the other hand, if application flexibility, output stability, and longevity are important parameters, then LED lighting might be more appropriate. Depending on the exact lighting requirements, oftentimes more than one source type may be used for a specific implementation, and most vision experts agree that one source type cannot adequately solve all lighting issues. It is important to consider not only a source's brightness, but also its spectral content. Microscopy applications, for example often use a full spectrum quartz halogen, xenon, or mercury source, particularly when imaging in color; however, a monochrome LED source is also useful for B&W CCD camera, and also now for color applications, with the advent of "all color – RGB" and white LED light heads. In those applications requiring high light intensity, such as high-speed inspections, it may be useful to match the source's spectral output with the spectral sensitivity of your particular vision camera. For example, CMOS sensor-based cameras are more IR sensitive than their CCD counterparts, imparting a significant sensitivity advantage in light-starved inspection settings when using IR LED or IR-rich Tungsten sources.

Vendors must be contacted to recommend proper lighting relative to the job to be accomplished.

USES FOR MACHINE VISION

Even though we have seen several uses for MV, I want now to give additional insights as to how this technology can be used for seemingly "mundane" yet important work relating to quality.

There are many uses for machine vision with more applications becoming possible each year. Applications produce advancement in technology both hardware and software. A growing need for smaller and more advanced cameras, as well as software to process those images, results each year. Uses for machine vision generally fall within the categories given below.

Inspection

- **Color matching**—Very often, color is the only characteristic that differentiates parts such as bottle caps, containers and pharmaceuticals. In the auto industry, suppliers find that human inspectors have a difficult time in verifying that side-view mirrors are assembled on the correct car body. Humans often mismatch colors, while color vision tools can reliably distinguish between them. When color is the most unique aspect of the part, color vision can be used to determine if an item is good or bad. For example, verifying that a red-light emitting diode (LED) is present and bright enough or was properly assembled. Sixteen-bit color resolution allows systems to recognize 65,000 individual colors—plenty for most applications. But applications where color variations are more subtle may require more sensitive twenty-four-bit color resolution, which enables the system to see sixteen million individual color variations...more than can be detected by the human eye.

FIGURE 18: COLOR MATCHING AUTOMOBILE FUSES

Another example is the color matching given by Figure 17 above. In this case, automobile fuses are placed in the proper sequence by the capacity of the fuse represented by colors.

As another example, consider the inspection of baked goods such as hamburger buns, English muffins, or tortillas. These baked products are sent by conveyer belt through an inspection station. At the inspection station a laser profiler measures the product's three-dimensional structure and a bright light and a color camera are used to measure product color. The product moves quickly, so the bright light is needed to give the camera enough reflected photons to form an image. The color image of the baked goods is examined to ensure that it exhibits the proper colors. Obviously incorrect colors, say green or orange, might indicate mold or contamination and must cause product rejection. More subtle are colors that suggest to us that the baked goods are properly cooked. Consider "toast marks," on English muffins for example. English muffins are baked in tins and the heel (bottom) appears brown with black marks. The heel also has a dusting of farina or corn meal to prevent the muffin from sticking to the tin and to add taste and visual texture.

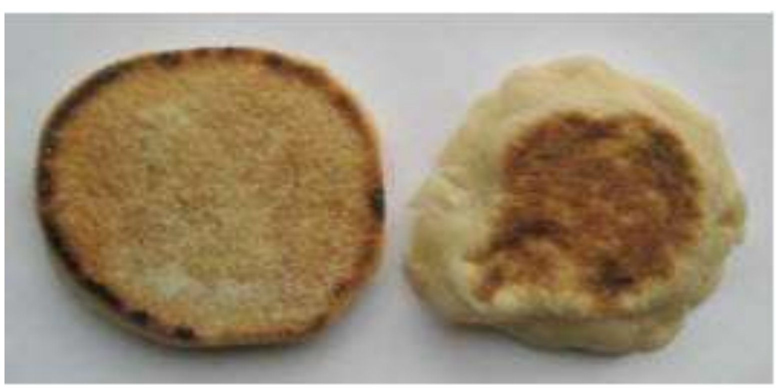

FIGURE 19: INSPECTION OF BAKED GOODS

FIGURE 20: INSPECTION OF COOKIES MOVING RAPIDLY DOWN CONVEYOR LINE

- **Sub-Assembly Verification--** Assembly verification involves the use of custom machine vision systems recognizing one or more features of the parts being verified. Along with the vision system itself, additional logic is often required to perform the appropriate task following verification. This may involve: 1.) Verifying the presence of one or more parts or features, 2.) Checking alignment precision of subassemblies, 3.) Verifying feed rates and counts for production systems, 4.) Automated rejection of parts, based on quality metrics. Machine vision is being used extensively in the inspection of electronic PC boards to ensure the boards have been "stuffed" with the correct number and type of component. Pattern finding and presence/absence for locating and identifying parts on an assembly is critical to the electronics industry. Figure 21 below shows the complexities of PC boards as they may exist today. Try verifying the presence of components eight hours per day, five days per week to ensure the proper component is in the proper slot.

FIRURE 21: PC BOARD "STUFFING" AND COMPONENT INSPECTION

An additional use is verifying all components, belts, pulleys, etc are located properly on an automobile engine prior to that engine being installed in a vehicle. MV would be a great asset here and would allow documentation that proper assembly was carried out.

FIGURE 22: VERIFICATION OF COMPONENTS FOR AUTOMOTIVE INDUSTRY

- **Asset Tracking—** Asset tracking software provides an efficient, cost-effective method to track fixed-asset inventories of capital equipment, computers and furniture, and to calculate depreciation. This can certainly allow the user to label each asset with a unique barcode, and identify descriptors, including serial number, cost, purchase date, and date received. Specific software can also track the maintenance status of capital assets. Asset data is collected with an easy-to-use handheld portable data assistant (PDA) or a portable data collection terminal (PDTs) with barcode or RFID scanner.

- **Material Inspection--** One of the most important tasks in the manufacture of car-seat assemblies is checking whether the correct fabric has been placed on both the car seat and the headrest. Since the placement of incorrect fabrics cannot easily be discerned by human operators, the systems developed are performing this function. To perform fabric inspection of each headrest, for example, images of the fabric are first digitized into the system's PC. After each individual image is digitized, a region of interest is applied to the image, which is then processed using a 9 × 9 erosion filter to enlarge the black objects within the image. This has the effect of increasing the intensity of the fabric's weave.

FIGURE 23: CHECK FABRIC WEAVE AND COLOR FOR AUTOMOBILE CAR SEATS

Another use of MV is determining if there are any imperfections in materials such as described by the graphic below:

FIGURE 24: HIGH SPEED MATERIAL WITH FOUR IMAGING SYSTEMS INSPECTION

The material could be vinyl, carpet or cloth fabric. The point being the product is continuously inspected.

- **Counting**-- Count the number of welds, teeth, slots or other features critical to an assembly or subassembly of components. When you are producing very high speeds it's doubly important to accomplish an accurate count. That count can include off-quality products as well. In this fashion, trends may be noticed and sigma numbers developed. In the figure below, the number of teeth on a mill is being counted.

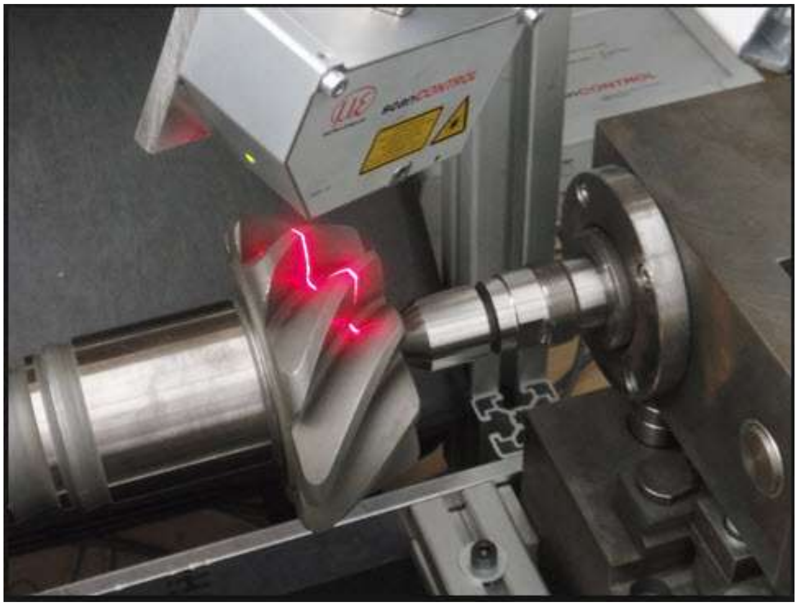

FIGURE 25: COUNTING TEETH ON A MILLING TOOL

- **Check for surface defects before painting**--For high-speed automotive parts this is an absolute necessity and insures value-added to finished goods.

- **Determine the location, diameter and roundness of a hole placement--** Verification of placement and roundness of holes in a component or subassembly can save countless hours of inspection and gauging that otherwise would be done manually.

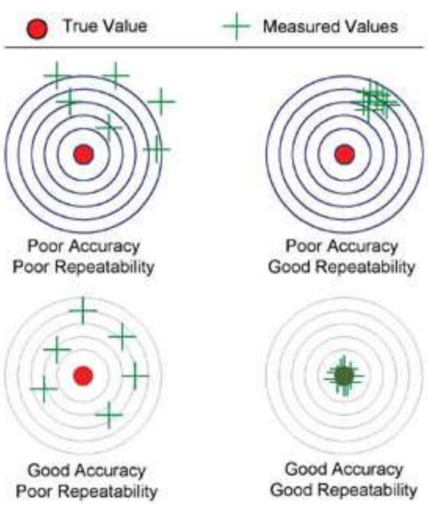

FIGURE 26: ROUNDNESS AND ACCURACY OF HOLES

- **Location & alignment for pick and place—** Imagine a high-speed operation in which components are selectively placed into a substrate. A good example of this is a printed circuit board. As you know, holes and slots are punched into each board at predetermined and precise locations to accept diodes, capacitors, resistors, etc. If the hole dimensions are off relative to baseline dimensions, the automated processes of pick and place are useless and yield off-quality parts.

- **Ball grid array inspection—** A fully-developed machine vision system can provide some of the critical factors for ball grid array (BGA) quality evaluation, such as the height of solder ball, diameter, pitch and co-planarity. The BGA is descended from the pin grid array (PGA), which is a package with one face covered (or partly covered) with pins in a grid pattern which, in operation, conduct electrical signals between the integrated circuit and the printed circuit board(PCB) on which it is placed. In a BGA the pins are replaced by pads on the bottom of the package, each initially with a tiny ball of solder stuck to it. These solder spheres can be placed manually or by automated equipment, and are held in place with a tacky flux. The device is placed on a PCB with copper pads in a pattern that matches the solder balls. The assembly is then heated, either in a reflow oven or by an infrared heater, melting the balls. Surface tension causes the molten solder to hold the package in alignment with the circuit board, at the correct separation distance, while the solder cools and solidifies, forming soldered connections between the device and the PCB. With the number of electro-mechanical devices used today and high-speed technology accomplishing the assembly, machine vision is critical to providing quality in this area.

FIGURE 27: BALL GRID ARRAY

- **Barcode reading and verification**—We've already discussed barcode reading but it's worth another look. A barcode is a machine-readable symbol that can be printed on a label and applied (print-and-apply) or directly marked (DPM) on a part, product, or package. Typically, the barcode contains encoded data about that specific item (unique item identification or serialization) or contains encoded data about a batch or lot of items. Barcode scanners are used to capture and read this data to track and identify parts throughout the supply chain. In production this data can be used to automate operations, enable quality control, and save time, money, and manpower for manufacturers. Machine vision is the automated extraction of useful information from digital images. In an industrial setting, machine vision systems take the capabilities of barcode imaging technology a step further, using image capture and analysis to automate tasks such as inspection, gauging, and counting - in addition to reading barcodes and optical characters. Machine vision systems have helped manufacturers worldwide improve product quality, decrease costs, and ensure customer satisfaction. Smart cameras and PC-based vision systems are standard in automated inspection systems. While human inspectors can visually inspect parts to judge the quality of workmanship, machine vision systems use advanced hardware and software components to perform similar functions at higher speeds, reliably, and with greater precision. One critical use for barcode reading is given with the figure below.

FIGURE 28: BARCODE READING OF PHARMACEUTICALS

- **Quality Checking—**In each example given above the object is improvement in the quality of manufactured and assembled components. Generally, machine vision is utilized when high-speed assembly, counting, barcode reading, etc is necessary and warranted.
- **Package Integrity—**Packaging inspection includes the following areas of interest:
    - Label and print inspection including label positioning, label quality, making sure correct label is on product.
    - Carton and box content inspection. Detection of dents, tears and missing pieces.
    - Meat and cheeses rely on flat trays covered by plastic film which, unless flawed or torn, keeps the product fresh and free from contamination. Seal inspection vision systems detect holes or tears in plastic film, preventing products at risk of

contamination from reaching retailers. Product caught in the seal is also detected, ensuring that packages are properly sealed and safe.

FIGURE 29: PACKAGING INSPECTION USING MV TO INSURE AIR-TIGHT SEAL

- Food and code reading. Food manufacturing is one of the most heavily regulated industries in the world. The ability to track food products through every step of the production process is reliant on barcodes and lot codes which make recalls go quicker and easier. Vision inspection systems perform inspections of 1D and 2D barcodes for readability and accuracy, and OCR capabilities perform the same inspections on lot codes.

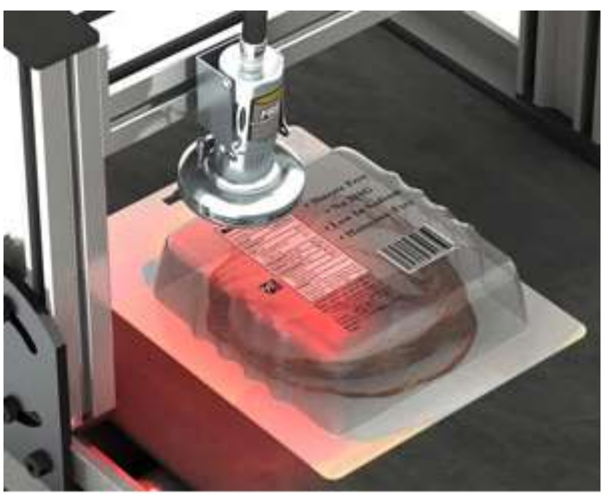

FIGURE 30: READING LABELING ON PACKAGED MEAT PRODUCTS

Gauging and Metrology—First, let us define metrology. Metrology, the science of measurements, includes all aspects both theoretical and practical with reference to measurements, whatever their uncertainty, and in whatever fields of science or technology they occur. Thus, metrology is also the science of measurement associated with the evaluation of its uncertainty. It is important to understand that only to measure is not the sole purpose of metrology but the core of metrology lies in the validation of the result, particularly by specifying its actual limitations. Metrology is not restricted only to standards of length and mass but other parameters in sectors of social concern, such as health, safety, and environmental protection also.

It is a technique by which visual sensory inputs can be obtained and processed in a manner, such that meaningful information about the image is generated. The availability of microprocessors coupled with advanced pattern recognition software makes machine vision an industrial reality. Machine vision systems perform the functions of image sensing, image analysis and image interpretation. These systems have ability to automatically acquire data about an object, measure image features, recognize objects and make appropriate decisions.

Engineers first used machine vision for measurement and often seriously underestimated the number of pixels required to achieve a desired level of measurement precision uncertainty. In fact, it may require multiple cameras, specialty cameras such as line scan imagers, or multiple views of a single part to achieve the required resolution for the specified inspection tolerance. Sometimes we can squeeze out additional resolution in an imaging system mathematically using algorithms that report features to sub-pixel repeatability. Some examples would be gray-scale edge analysis, geometric or correlation searching, regressions such as circle or line fitting, and connectivity in some cases. If one can take into account sub-pixel results through the use of these tools, then the smallest unit of measurement can be less than a single pixel, described earlier. Note though, that estimates provided by vendors for sub-pixel capability are only that, and usually are made for best-case imaging, optics, and part presentation. Take care in using arbitrary sub-pixel expectations as a determining factor for specifying system measurement capability. Test the system with actual parts and images to empirically determine the sub-pixel capability.

Guidance-- Robotic guidance and positioning would be extremely difficult without machine vision in some instances. Industrial applications using robotic systems have been in use for years. A part is placed in a fixture, secured, and then enable switches are activated allowing a robot to perform the necessary task. The tasks are programmed into the processing unit of the control. Movements never vary from part to part. That's well and good, but what if you are performing surgery using robotic systems? You MUST have "eyes" on the patient. Machine vision gives us that capability.

The goal of using robots in medicine is to provide improved diagnostic abilities, a less invasive and more comfortable experience for the patient, and the ability to do smaller and more precise interventions.

Robots are currently used not just for prostate surgery, but for hysterectomies, the removal of fibroids, joint replacements, open-heart surgery and kidney surgeries. They can be used along with MRIs to provide organ biopsies. Since the physician can see images of the patient and control the robot through a computer, he/she does not need to be in the room, or even at the same location as the patient.

This means that a specialist can operate on a patient who is very far away without either of them having to travel. It can also provide a better work environment for the physician by reducing strain and fatigue. Surgeries that last for hours can cause even the best surgeons to experience hand fatigue and tremors, whereas robots are much steadier and smoother.

FIGURE 31: ROBOTIC SURGERY PERFORMED USING MV TECHNOLOGY AND GUIDANCE

Identification and Verification

We have already discussed facial recognition and security relative to machine vision but a brief repeat may be necessary.

Facial Recognition—Again, facial recognition is a very specific technology becoming much more important in our society today. The science depends upon a data base of photographs in which comparisons are made from scanned video or "stills". Specific facial features are compared that bring about identification. As mentioned earlier, the two criminals perpetrating the Boston bombing were captured by video cameras and identified by facial recognition technology. We have given examples of facial recognition in the introductory part of this course and will not belabor the point. Facial recognition is one of several biometric suite options available to law enforcement.

Security--Video surveillance has proven itself to be a significant benefit for a range of uses. There are very few retail operations that do not have some form of video surveillance throughout their facility. Many traffic intersections now have recording video used to gather information relative to movement of automobiles and trucks. Liability cases involving moving vehicles after wrecks and damage have more than once been settled as a result of video recording the exact time and detailing who might be at fault. My youngest granddaughter attended day care with internal video present. Her parents could monitor her activities by logging on and indicating the correct user's name and password. Every activity could be monitored.

Serving as a remote set of eyes, video surveillance allows a virtual presence in off-site locations from a single point. What's more, video cameras cover a large contiguous swath of view, allowing a panning camera to steadily and consistently sweep a search pattern.

Video systems can also function in locations where humans cannot. The earliest known video surveillance technology was used to safely monitor the development and launch of V-2 rockets in 1942. From a safe distance, scientists and engineers could observe performances and identify failures.

Since then, video systems have acted as an extension of our eyes and ears. A steady stream of technology developments and manufacturing advancements have taken video surveillance to such a level that we feel comfortable relying on it for security purposes.

Due to several events involving law enforcement, chest video cameras in some cities are worn by officers during patrol. These are recording cameras that capture the true events when dealing with difficult situations.

For decades, video was limited to monochrome sensing and displaying of images in real time. Color filters in front of each sensor limited the analog level to the intensity of the constituent colors in order to create color sensors. Color phosphors placed in the path of the electron beam were used to create colors. The advent of color-burst crystals helped to synchronize color components in the video signals.

Steady advances produced improvements in these tubes over time bringing about better resolutions, lower power, lower cost manufacturing, and higher reliabilities. The Closed-Circuit Television (CCTV) and broadcast industries were born and driving development at an even quicker pace

On the downside, these technologies used fragile glass and the circuitry needed used higher voltages. Size constraints made tube-based image sensors a large and bulky assembly. Thanks to modern semiconductor technology, this is no longer the case.

Security and surveillance are increasingly a part of our everyday lives. We are photographed, taped, and monitored in nearly everything we do. The sheer number of cameras and video feeds has driven the need for security personnel to sit and watch and make determinations.

Today's hardware systems cameras and video aggregators will continue to use higher-level processing and even AI to automate the data gathering and security assessments.

Bar Code Data Matrix-- A Data Matrix code is a two-dimensional matrix barcode consisting of black and white "cells" or modules arranged in either a square or rectangular pattern. The information to be encoded can be text or numeric data. Usual data size is from a few bytes up to one thousand five hundred and fifty-six (1556) bytes. The length of the encoded data depends on the number of cells in the matrix. Error correction codes are often used to increase reliability: even if one or more cells are damaged so it is unreadable, the message can still be read. A Data Matrix symbol can store up to 2,335 alphanumeric characters.

Data Matrix symbols are rectangular in shape and usually square and are composed of "cells": little squares that represent bits. Depending on the coding used, a "light" cell represents a zero (0) and a "dark" cell is a one (1), or vice versa. Every Data Matrix is composed of two solid adjacent borders in an "L" shape (called the "finder pattern") and two other borders consisting of alternating dark and light "cells" or modules (called the "timing pattern"). Within these borders are rows and columns of cells encoding information. The finder pattern is used to locate and orient the symbol while the timing pattern provides a count of the number of rows and columns in the symbol. As more data is encoded in the symbol, the number of cells (rows and columns) increases. Each code is unique. Symbol sizes vary from 10×10 to 144×144 in the new version ECC 200, and from 9×9 to 49×49 in the old version ECC 000 - 140.

The most popular application for Data Matrix is marking small items, due to the code's ability to encode fifty characters in a symbol that is readable at 2 or 3 mm^2 and the fact that the code can be read with only a 20% contrast ratio. The Data Matrix is scalable, with commercial applications as small as 300 micrometers (laser etched on a six hundred (600) micrometer silicon device) and as large as a one (1) meter (3 ft) square (painted on the roof of a boxcar). Fidelity of the marking and reading systems are the only limitation.

FIGURE 32: BARCODE AND DATA MATRIX

I think we all have application software on our cell phones that allow us to integrate barcode data.

Gauging and Metrology-- A determining factor for delivering high precision and low uncertainty in machine vision metrology is the resolution of the acquired image. In this context, the term *resolution* (or *image* resolution) means the size of an individual pixel in real-world units. Simply put, if a camera sensor contained 1000 pixels in the horizontal direction, and optics were incorporated that acquired an image that covered an area in the real-world scene that was one (1) inch in width, a single pixel would represent 0.001". Note that this is a fundamental metric that does not change with camera manufacturer or analysis software.

As a gauge, the smallest unit of measurement (some exceptions noted later) in a machine vision system is the single pixel. As with any measurement system, in order to make a repeatable and reliable measurement one must use a gauge where the smallest measurement unit (as a general rule of thumb) is one tenth of the required measurement tolerance band. In the example just described, the system could be estimated to provide a precision measurement to approximately +/- 0.005" (a tolerance band of 0.01", ten times the gauge unit).

Engineers first using machine vision for measurement often seriously underestimate the number of pixels required to achieve a desired level of measurement precision uncertainty. In fact, it may require multiple cameras, specialty cameras such as line scan imagers, or multiple views of a single part to achieve the required resolution for the specified inspection tolerance.

Imaging is a function of optics and lighting (and as we will discuss later, part presentation). For most applications, the only optics used will be a lens assembly, but the selection of that lens is critical to the metrology application. Beyond delivering an image of the proper real-world size to the sensor, for metrology the lens must reproduce the image as accurately as possible without distortion. Furthermore, lenses have a resolution metric as well, which often is specified as line pairs per mm or inch (lp/mm, lp/in), and by extension may have a specification for MTF (modulation transfer function) or more simply the ability of the lens to produce high contrast at high lp/mm. The higher the pixel count, the more important these lens metrics become. Ensure that the specified optics are high-quality, high-resolution products designed for machine vision applications.

For applications that require a very small field of view (for example less than a few millimeters), consider the use of microscope optics and/or high-magnification optics specially made for machine vision. These are available from a number of vendors. It is not recommended that standard optics be pushed to higher magnification using extenders or add-on magnification.

ANNUAL SALES ON A GLOBAL BASIS:

GLOBAL MARKETS

The global machine vision market size was valued at 12.29 billion in 2020 and is expected to expand at a compound annual growth rate (CAGR) of 6.9% from 2021 to 2028. The increasing demand for quality inspection and automation in different industrial verticals is likely to drive the market for machine vision. Additionally, the need for vision-guided robotic systems across the automotive, food and beverage, pharmaceutical and chemical, and packaging segments is expected to fuel the market growth. The surge in demand for application-oriented machine vision (MV) systems is also expected to boost the adoption of the technology over the forecast period. MV systems involve the ability of a computer to observe, inspect, and scrutinize the work performance by employing one or more video cameras, digital signal processing, and analog to digital conversion. The captured data is then transferred to the computer to analyze and provide the desired output. Resolution and sensitivity are two important aspects of any MV system. Resolution is responsible for differentiating between objects whereas sensitivity is the machine's ability to detect objects or weak impulses despite dim lights or invisible wavelengths.

The technology is witnessing high adoption in industrial operations and is significantly replacing manual inspection and measurements owing to the increasing necessity for efficient and reliable inspection and measurements. Machine vision systems deploy smart cameras and image processing to perform measurements and inspections.

The intensifying need for superior inspection and increasing automation are the key influencing factors paving the way for the notable adoption of machine vision technology. Furthermore, the need for increased quality control among consumers and manufacturers, coupled with the government regulations to abide by the prescribed specifications, is expected to catapult the adoption of machine vision technology. If we look at a digital, we see the following:

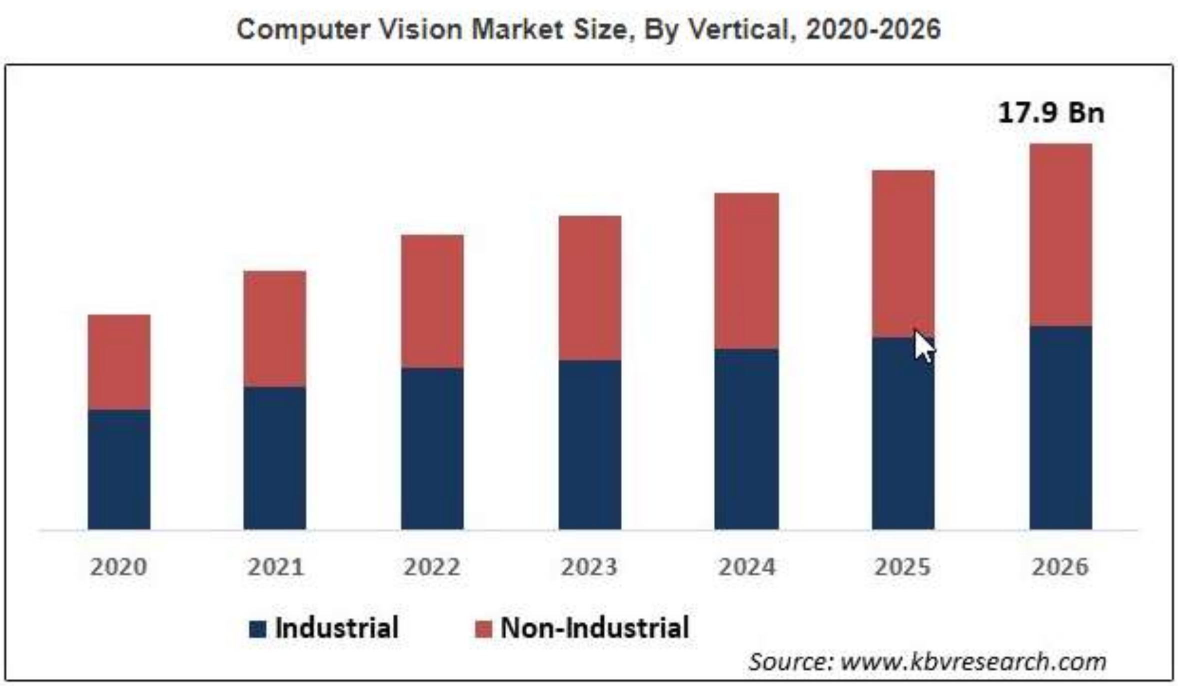

FIGURE 33: COMPUTER VISION MARKET SIZE, BY VERTICAL 2020—2026

A conglomerate summary is as follows:

Computer Vision Market Report Coverage

Report Attribute	Details
Market size value in 2019	USD 10.5 Billion
Market size forecast in 2026	USD 17.9 Billion
Base Year	2019
Historical Period	2016 to 2018
Forecast Period	2020 to 2026
Revenue Growth Rate	CAGR of 10.1% from 2020 to 2026
Number of Pages	278
Number of Tables	443
Report coverage	Market Trends, Revenue Estimation and Forecast, Segmentation Analysis, Regional and Country Breakdown, Competitive Analysis, Companies Strategic Developments, Company Profiling
Segments covered	Product Type, Component, Application, Vertical, Region
Country scope	US, Canada, Mexico, Germany, UK, France, Russia, Spain, Italy, China, Japan, India, South Korea, Singapore, Malaysia, Brazil, Argentina, UAE, Saudi Arabia, South Africa, Nigeria
Growth Drivers	• Rising demand for edge computing in mobile devices • Development of Machine Learning regarding Vision Technology
Restraints	• Lack of Awareness and Technical Knowledge

FIGURE 34: COMPUTER VISION MARKET REPORT COVERAGE

The technology is gaining considerable traction across food and packaging, automotive, pharmaceutical, and other industrial verticals owing to abilities such as improved detection of objects, enhanced analysis, monitoring tolerance, and accurate component measuring.

All these factors are expected to boost the market growth over the forecast period. However, the lack of efficient system operators due to inadequate training is likely to obstruct the smooth growth of the market.

The outbreak of COVID-19 has adversely impacted the economic condition due to government measures such as lockdown and border closures, leading to delays in procurement, manufacturing, and delivery. China, being one of the first countries in Asia to start its economic activity, has seen a recovery trend in its economic progress. On the other hand, the U.S. and Europe having a positive turnaround, the economic trend remained sluggish.

In 2020, the hardware segment accounted for the largest share of more than 60.0% and is anticipated to dominate the market over the forecast period. On the basis of offering, the market has been segregated into hardware, software, and services.

Hardware components comprise several objects such as cameras, frame grabbers, optics/lenses, LED lightings, and processors. Cameras held the largest share in 2020, which is attributed to the increasing demand for CMOS imaging sensors. This, in turn, is anticipated to result in the growth of the hardware sub-segment.

The software offerings are bifurcated into application-specific MV software and deep learning MV software sub-categories. The market for software is application-specific and fragmented based on the necessity of application. The software segment is expected to register a steady growth rate over the forecast period on account of the training and deep learning of the technology, which is fairly contributing to the overall market growth.

The deep learning software sub-segment is anticipated to expand at the highest growth rate over the forecast period owing to the increasing demand for the smart machine vision systems that are equipped with the capabilities of reacting smartly based on the necessity of the operation across different industry verticals.

Additionally, in the services segment, machine vision providers offer mainly two types of services, namely integration and solution management. Machine vision system integrators are used for inspection, testing, assembly, and gaging applications that help customers to meet their product specifications. Moreover, solution management is used for single-step debug operations, inspection control (start and stop), and open and save solutions.

The offering segment is anticipated to exhibit a steady growth rate over the forecast period owing to the large market share of the hardware components. The hardware offering is expected to continue growing over the forecast period. The software sub-segment is expected to progressively contribute to the overall industry growth and help drive the market.

Product Insights

In 2020, the PC based segment held the largest share of exceeding fifty-fiver percent (55.0%), and is expected to exhibit a significant CAGR from 2021 to 2028. The segment is anticipated to continue growing and lead the market in terms of revenue over the forecast period. The product segment has been sub-categorized into PC based and smart camera-based systems.

The smart camera-based systems are projected to exhibit the fastest growth rate of seven-point two percent (7.2%) over the forecast period. This considerable growth of the segment is attributed to the growing adoption of cameras in 3D imaging.

Machine vision systems, also called vision systems, consist of numerous cameras. At times, depending upon the requirements, these cameras are mounted over the assembly lines so as to observe and examine products and capture data. This is leading to the greater adoption of smart cameras in these systems.

Cameras are also capable of reading labels and directing products automatically without any human involvement. Minimized human intervention has led to decreased errors and increased accuracy of inspecting labels and tags. These aspects of smart cameras are influencing the adoption of the technology across various industrial sectors, thereby fueling up the overall market growth.

Application Insights

In 2020, the quality assurance and inspection segment held the largest share of over 51.0% and is expected to exhibit a significant CAGR from 2021 to 2028. On the basis of application, the market has been segmented into quality assurance and inspection, positioning and guidance, measurement, and identification. The systems are extensively used for scanning and identifying labels, barcodes, and texts, especially in the packaging sector. This automates packaging activities, thereby saving time, avoiding human errors, and increasing efficiency.

The technology is frequently used in the consumer goods, pharmaceutical, and packaging sectors. The adoption of technology in these sectors has resulted in reduced counterfeit products to a large extent, eventually driving the overall market.

Identification using machine imaging is also used in camera surveillance, monitoring traffic, or recognizing number plates for security purposes. The segment is expected to expand at the fastest CAGR of seven-point nine percent (7.9%) from 2021 to 2028 owing to several advantages and opportunities offered to the technology worldwide.

End-use Industry Insights

In 2020, the automotive end-use industry held the largest share of nineteen-point three eight percent (19.38%) and is expected to witness considerable growth from 2021 to 2028. On the basis of the end-use industry, the market has been categorized into automotive, pharmaceuticals and chemicals, electronics and semiconductor, pulp and paper, printing and labeling, food and beverage (packaging and bottling), glass and metal, postal and logistics, and others. Currently, the automotive industry is the largest adopter of machine vision systems worldwide and is expected to expand at a steady growth rate over the forecast period.

Machine vision in the automotive industry is extensively used for inspection purposes, which include presence-absence checking, error proofing, assembly verification, and final inspection. Besides, MV systems are used for dimensional gauging, robotic guidance, and testing automation purposes, which comes under the measure, gauge, and guide applications. Therefore, the demand for mechanized imaging is significant across the automobile sector and is anticipated to continue growing steadily over the coming years.

Regional Insights

Asia Pacific dominated the market with a share of forty-point two seven percent (40.27%) in 2020. The region is projected to witness considerable growth from 2021 to 2028. This can be accredited to the lucrative opportunities in automotive, packaging, pharmaceutical, and other industrial applications in the Asia Pacific region.

As the region is establishing itself to become a global manufacturing hub, the technology is anticipated to gain significant traction over the forecast period. China and Japan are prominent countries having the potential to offer extensive opportunities for emerging as well as matured technologies, such as machine vision. The numerous manufacturing industries are contributing to the growth and prosperity of the region’s overall economic development.

In addition to this, the expenditure and operational benefits, coupled with the initiatives being undertaken by the governments of emerging countries, such as South Korea, India, Taiwan, and

Singapore, are responsible for catapulting investments and encouraging different industry players to establish their production units in the Asia Pacific region.

Furthermore, increasing investments are being carried out in R&D activities to improve machine vision technology and related developments due to which prominent players are undertaking strategic initiatives, such as distribution alliances, partnerships, mergers, and acquisitions. As such, all these factors are expected to propel the growth of the market in the Asia Pacific region.

COST OF OPERATION: Any company must balance potential benefits with initial costs and cost of operation over time. Most will capitalize the expenditures for MV components, software and overall systems. The table below will indicate cost of equipment and a twenty percent (20%) contingency allowance.

Preliminary system development costs ranged from $14,450.00 for basic equipment without software to $84,500.00 for the most complete budget proposal. Four vendors shown in the table below submitted cost estimates for a complete design-build project that ranged from $50,000.00 to $84,500.00. There are many unknown design features that would surface during a properly funded design-build contract making it difficult to forecast an exact purchase price. Consequently, allowing for variation in the final system specifications, it would be reasonable to anticipate that the preliminary cost estimates could increase by as much as 20% for an installed system

Design-Build Project Cost

VENDOR	ESTIMATE	20% INCREASE
Novacam	$84,500.00	$101,400.00
Saber	$50,000.00	$60,000.00
Webview	$75,000.00	$90,000.00
Wintriss Engineering	$75,000.00	$90,000.00

A diverse range of machine vision inspection vendors were contacted for this cost study. From the vendor responses several points became clear:

- The technology exists to duplicate the human inspection and analysis process for evaluating the surface quality of the star mold castings.
- There are enough qualified vendors within the United States and worldwide with the experience and the technology to allow for competitive and creative response to a request for proposal (RFP).
- Careful preparation of the statement of work (SOW) is critical to achieving the desired level of inspection accuracy, precision and functionality. It cannot be stressed enough that the human inspection process be documented and quantified in process standards for the part to be inspected. Acceptance and rejection criteria must be spelled out in the process standards to allow ready development of

algorithms and software. Finally, the SOW must clearly communicate exactly how the acquired data are to be used and how those data are to be reduced down to meaningful displays and reports.

STANDARDS: There are several standards existing in the industry today. These are as follows:

- **GigE Vision - True Plug and Play Connectivity--** GigE Vision® is a global camera interface standard developed using the Gigabit Ethernet communication protocol. GigE Vision allows for fast image transfer using low-cost standard cables over very long lengths. With GigE Vision, hardware and software from different vendors can interoperate seamlessly over GigE connections.

- **Camera Link – The Only Real-Time Machine Vision Protocol--** Camera Link® is a robust communications link using a dedicated cable connection and a standardized communications protocol. Camera Link is a hardware specification that standardizes the connection between cameras and frame grabbers. It defines a complete interface which includes provisions for data transfer, camera timing, serial communications, and real time signaling to the camera.

- **Camera Link HS - The Machine Vision Protocol Moving Forward--** Camera Link HS is designed to specifically meet the needs of vision and imaging applications. Its low latency, low jitter, real-time signals between a camera and a frame grabber carry image data and configuration data. The interface takes the key strengths of Camera Link and adds new features and functions to meet customer's demands today and tomorrow. The standard provides:

    - Scalable Bandwidths from 300 to 16,000 MB/s
    - Extremely Reliable Data Delivery
    - Copper or Fiber Optic Cables from 15 to 300+ meters in length
    - Multi-Vendor Compliant Components Available
    - IP Cores Available for Quick, Low-Cost Development

- **USB3 Vision - High Bandwidth Yet Simple Connectivity--** The USB3 Vision interface is based on the standard USB 3.0 interface and uses USB 3.0 ports that will soon be standard on most PCs (with Windows 7 service pack and Windows 8 native support expected soon). Components from different manufacturers will easily communicate with each other. The standard is currently in version 1.0.

    - High bandwidth in excess of 350 MB/s
    - Easy-to-use plug and play interface
    - Power and data over the same passive cable to five meters (more with active cables)
    - Uses GenICam™ generic programming interface

As mentioned, this is a very dynamic and growing technology. Standards, both domestic and global surface each year. Vendors selling into the marketplace are the best sources for current standards. In each city and state, local building and electrical codes take prescience. You MUST consult with the proper agencies for guidance.

MAJOR COMPANIES WITHIN THE TECHNOLOGY:

The following text is taken from Machine Vision Magazine and indicated the "major players" in the MV technology today. We will supplement their fine work with descriptions interspersed within the text.

Vision Systems Design's marketing department received hundreds of responses to our questionnaire about what our readers thought were the most important companies, technologies, and individuals that have made the most important contributions to the field of machine vision. Not surprisingly, many of the companies our readers deemed to have made the greatest impact have existed for over twenty years or more (Figure 1).

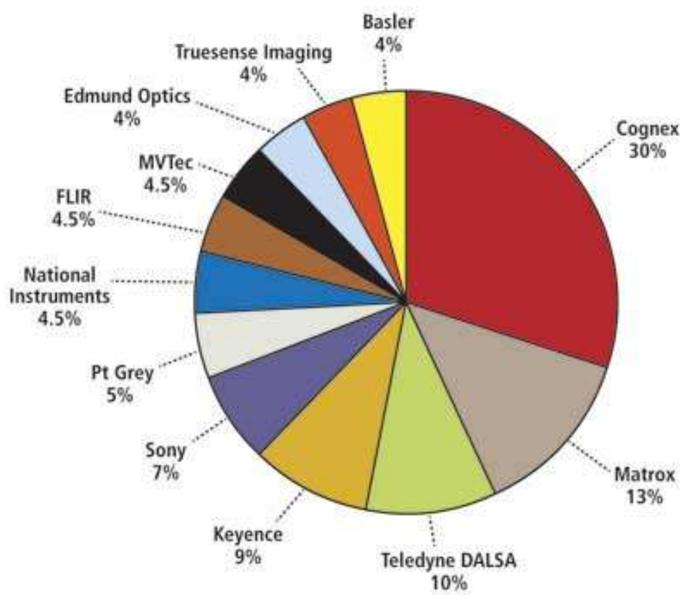

FIGURE 35: When asked which companies had made the greatest impact on the machine vision over the past twenty years or more, 30% of respondents chose Cognex.

Of these, Cognex (Natick, MA; **www.cognex.com**) was mentioned more than any other company, probably due to its relatively long history, established product line and large installed customer base. Formed in 1981 by Dr. Robert J. Shillman, Marilyn Matz and William Silver, the company produces a range of hardware and software products including VisionPro software and its DataMan series of ID readers.

When asked what technologies and products have made the most impact on machine vision, readers' answers were rather more diverse (Figure 2). Interestingly, the emergence of CMOS images sensors, smart cameras and LED lighting, all relatively new development in the history of machine vision, were recognized as some of the most important innovations.

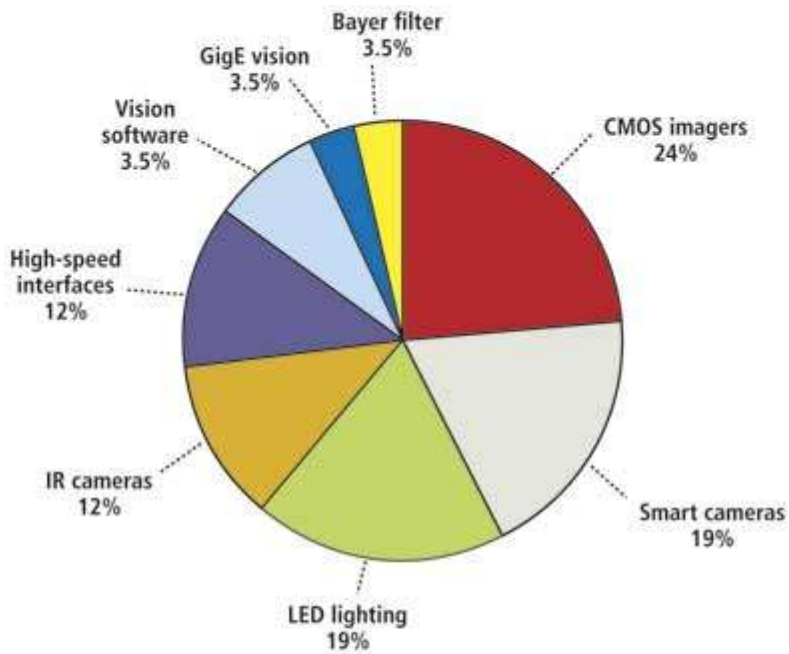

FIGURE 36: Relatively new developments in CMOS imagers, smart cameras and LED lighting were deemed to be the most important technological and product innovation.

As with any technology, there have been acquisitions and mergers along the way. The list below is recent as of 2019. As you know, 2020 was a very difficult year for all companies. MV concerns were no different.

Acquisition and Mergers:

- Oct-2019: Cognex acquired SUALAB, a leading Korean-based developer of vision software using deep learning for industrial applications. The acquisition accelerated Cognex's existing deep learning capabilities based on technology acquired from ViDi Systems.
- Sep-2019: TKH Group completed the acquisition of SVS-Vistek GmbH, the Machine vision camera manufacturer. The acquisition broadened TKH's portfolio of vision technology companies that includes Allied Vision, Chromasens, LMI Technologies, Mikrotron, NET, and Tattile.

- Sep-2019: TKH Group announced the acquisition of Lakesight Technologies, a global vision technology company providing innovative high-end technologies for imaging systems. The acquisition helped the company in becoming the leader in the machine vision industry.
- Jul-2019: Matterport signed a definitive agreement to acquire Arraiy, the pioneer behind breakthrough machine learning and computer vision technology. The acquisition would integrate Arraiy's core engineering team into Matterport in support of the company's mission to build the industry's leading computer vision data platform.
- Jul-2018: Basler AG acquired all of the shares of Silicon Software GmbH, a globally recognized technology leader in the programming of FPGA processors. The acquisition broadened Basler's product portfolio for computer vision applications. By combining Basler's cameras with intelligent image acquisition cards from Silicon Software, customers can receive solutions from a single source, which allows pre-processing and on-board analysis of image data, and enables cost-cutting potential.
- Dec-2017: Omron Corporation completed the acquisition of industrial traceability and inspection provider, Microscan. The acquisition advanced Omron's interconnected, industrial Internet of Things (IoT) barcode scanning, and machine vision solutions.
- Mar-2017: Intel Corporation acquired Mobileye, a computer vision, and machine-learning specialist. The acquisition includes data analytics as well as mapping and localization technologies. This acquisition strengthened its position in the emerging vehicle systems and data services markets.

CONCLUSIONS:

As you can see, Machine Vision technology is ever-changing. I certainly hope this course gives you some insights relative to components, operation, and uses for MV so you will be able to approach a vendor or vendors relative to your specific application. The best approach for MV is to contact a reputable supplier of equipment AND software. Each case or each application is different so consultation is an absolute must. As you have seen, there are many applications for Machine Vision and you are only limited by your imagination when considering a specific use for MV. Hope you enjoyed this one.

APPENDIX

Glossary of Terms

References

APPENDIX

GLOSSARY OF TERMS

Acquisition

The manner in which outside information is brought into an analysis system.

Algorithm

A set of well-defined rules or procedures for solving a problem in a finite number of steps.

Application-Specific Machine Vision (ASMV)

A turnkey system that addresses a single specific application that one can find widely throughout industry or within an industry.

Aperture

In context of photography or machine vision, aperture refers to the diameter of the aperture stop of a photographic lens. The aperture stop can be adjusted to control the amount of light reaching the film or image sensor.

aspect ratio (image)

The aspect ratio of an image is its displayed width divided by its height (usually expressed as "x: y").

Barcode.

A barcode (also bar code) is a machine-readable representation of information in a visual format on a surface.

Blob discovery.

Inspecting an image for discrete blobs of connected pixels (e.g., a black hole in a grey object) as image landmarks. These blobs frequently represent optical targets for machining, robotic capture, or manufacturing failure.

Bitmap.

A raster graphics image, digital image, or bitmap, is a data file or structure representing a generally rectangular grid of pixels, or points of color, on a computer monitor, paper, or other display device.

Camera.

A camera is a device used to take pictures, either singly or in sequence. A camera that takes pictures singly is sometimes called a photo camera to distinguish it from a video camera.

Charge-coupled device.

A charge-coupled device (CCD) is a sensor for recording images, consisting of an integrated circuit containing an array of linked or coupled, capacitors. CCD sensors and cameras tend to be more sensitive, less noisy, and more expensive than CMOS sensors and cameras.

Charge-Injection Device (CID)

Specific fabrication scheme for solid-state image sensors. The photo-generated charge is sensed by injecting it from the sensor into the substrate.

CMOS.

CMOS ("see-moss") stands for complementary metal-oxide semiconductor, is a major class of integrated circuits. CMOS imaging sensors for machine vision are cheaper the CCD sensors but noisier.

Color.

The perception of the frequency (or wavelength) of light, and can be compared to how pitch (or a musical note) is the perception of the frequency or wavelength of sound.

Color blindness.

Also known as color vision deficiency, in humans is the inability to perceive differences between some or all colors that other people can distinguish

Color temperature

"White light" is commonly described by its color temperature. A traditional incandescent light source's color temperature is determined by comparing its hue with a theoretical, heated black-body radiator. The lamp's color temperature is the temperature in Kelvin at which the heated black-body radiator matches the hue of the lamp.

Computer vision

. The study and application of methods which allow computers to "understand" image content or content of multidimensional data in general.

Correlation
A process whereby two image segments are compared to determine their similarity or to find the position at which optimal similarity exists.

Contrast.

In visual perception, contrast is the difference in visual properties that makes an object (or its representation in an image) distinguishable from other objects and the background.

C-Mount.

Standardized adapter for optical lenses on CCD - cameras. C-Mount lenses have a back focal distance 17.5mm vs. 12.5mm for "CS-mount" lenses. A C-Mount lens can be used on a CS-Mount camera through the use of a 5mm extension adapter. C-mount is a 1" diameter, 32 threads per inch mounting thread (1"-32UN-2A.)

CS-Mount.

Same as C-Mount but the focal point is 5mm shorter. A CS-Mount lens will not work on a C-Mount camera. CS-mount is a 1" diameter, 32 threads per inch mounting thread.

Data matrix.

A two dimensional Barcode.

Depth of field.

In optics, particularly photography and machine vision, the depth of field (DOF) is the distance in front of and behind the subject which appears to be in focus.

Diaphragm.

In optics, a diaphragm is a thin opaque structure with an opening (aperture) at its centre. The role of the diaphragm is to stop the passage of light, except for the light passing through the aperture.

Digital Imaging

Conversion of a video picture into pixels by means of an A/D converter where the level of each pixel can be stored in a computer.

Edge detection

ED marks the points in a digital image at which the luminous intensity changes sharply.

Electromagnetic interference.

Radio Frequency Interference (RFI) is electromagnetic radiation which is emitted by electrical circuits carrying rapidly changing signals, as a by-product of their normal operation, and which causes unwanted signals (interference or noise) to be induced in other circuits.

FireWire.

FireWire (also known as i. Link or IEEE 1394) is a personal computer (and digital audio/video) serial bus interface standard, offering high-speed communications. It is often used as an interface for industrial cameras.

Frame grabber

A frame grabber is a component of a computer system designed for digitizing analog and digital video signals

Field of view.

The field of view (FOV) is the part which can be seen by the machine vision system at one moment. The field of view depends from the lens of the system and from the working distance between object and camera.

Focus.

An image, or image point or region, is said to be in focus if light from object points is converged about as well as possible in the image; conversely, it is out of focus is light is not well converged. The border between these conditions is sometimes defined via a circle of confusion criterion.

Gaging (or Gauging)

In machine vision, non-contact dimensional examination of an object.

General-Purpose Vision System (GPMV)

A vision system that can be configured or adapted to many different applications.

Grayscale

A grayscale digital image is an image in which the value of each pixel is a single sample. Displayed images of this sort are typically composed of shades of gray, varying from black at the weakest intensity to white at the strongest, though in principle the samples could be displayed as shades of any color, or even coded with various colors for different intensities.

GUI.

A graphical user interface (or GUI, sometimes pronounced "gooey") is a method of interacting with a computer through a metaphor of direct manipulation of graphical images and widgets in addition to

Guidance
Deriving properties in an image to describe a position at various points in time.

HSV color space.

The HSV (Hue, Saturation, Value) model, also called HSB (Hue, Saturation, Brightness), defines a color space in terms of three constituent components:

- **Hue, the color type (such as red, blue, or yellow)**
- **Saturation, the "vibrancy" of the color and colorimetric purity**
- **Value, the brightness of the color**

Identification
The process of specifically identifying an object from a large class of objects through reading symbols.

IEEE 1394
The IEEE 1394 standard is a digital interface that will integrate the worlds of consumer electronics and personal computers by defining a backplane physical layer and a point-to-point cable-connected virtual bus implementation.

Image Analysis
Process of generating a set of descriptors or features on which a decision about objects in an image is based.

Image Processing

Transformation of an input image into an output image with desired properties.

Inspection
Non-destructive examination of a workpiece to verify conformance to some criteria.

Infrared imaging.

See Thermographic camera.

Incandescent light bulb

An incandescent light bulb generates light using a glowing filament heated too white-hot by an electrical current.

JPEG.

JPEG (pronounced jay-peg) is a most commonly used standard method of lossy compression for photographic images.

Lens.

A lens is a device that causes light to either converge or concentrate or to diverge, usually formed from a piece of shaped glass. Lenses may be combined to form more complex optical systems as a Normal lens or a Telephoto lens.

- **Lighting**.
- **Metrology**
- **Metrology is the science of measurement. There are lots of applications for machine vision in metrology.**
- **Machine Vision**.
- **(MV) is the application of computer vision to industry and manufacturing.**
- **Neural network**.
- **A NN is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network.**

Normal Lens.

In machine vision a normal or entrocentric lens is a lens that generates images that are generally held to have a "natural" perspective (nearer objects appear larger, and farther objects smaller) compared with lenses with longer or shorter focal lengths. Lenses of shorter focal length are called wide-angle lenses, while longer focal length lenses are called telephoto lenses.

Optical Character Recognition.

Usually abbreviated to OCR, involves computer software designed to translate images of typewritten text (usually captured by a scanner) into machine-editable text, or to translate pictures of characters into a standard encoding scheme representing them in (ASCII or Unicode).

Pattern recognition.

This is a field within the area of machine learning. Alternatively, it can be defined as the act of taking in raw data and taking an action based on the category of the data. It is a collection of methods for supervised learning.

Pixel.

A pixel is one of the many tiny dots that make up the representation of a picture in a computer's memory or screen.

Pixilation.

In computer graphics, pixilation is an effect caused by displaying a bitmap or a section of a bitmap at such a large size that individual pixels, small single-colored square display elements that comprise the bitmap, are visible to the eye.

Prime Lens.

Mechanical assembly of lenses whose focal length is fixed, as opposed to a zoom lens, which has a variable focal length.

RGB.

The RGB color model utilizes the additive model in which red, green, and blue light are combined in various ways to create other colors.

Shutter.

A shutter is a device that allows light to pass for a determined period of time, for the purpose of exposing the image sensor to the right amount of light to create a permanent image of a view.

Shutter Speed. In machine vision the shutter speed is the time for which the shutter is held open during the taking an image to allow light to reach the imaging sensor. In combination with variation of the lens aperture, this regulates how much light the imaging sensor in a digital camera will receive.

Smart Camera-A smart camera is an integrated machine vision system which, in addition to image capture circuitry, includes a processor, which can extract information from images without need for an external processing unit, and interface devices used to make results available to other devices.

Systems Integrator

A company that provides a turnkey machine vision system, adapting the vision system to a specific customer's requirements.

SVGA.Super Video Graphics Array, almost always abbreviated to Super VGA or just SVGA is a broad term that covers a wide range of computer display standards.

Telecentric Lens-.

Compound lens with an unusual property concerning its geometry of image-forming rays. In machine vision systems telecentric lenses are usually employed in order to achieve dimensional and geometric

invariance of images within a range of different distances from the lens and across the whole field of view.

Telephoto Lens.-

Lens whose focal length is significantly longer than the focal length of a normal lens.

Thermography--.

thermal imaging, a type of Infrared imaging.

TIFF.

Tagged Image File Format (abbreviated TIFF) is a file format for mainly storing images, including photographs and line art.

USB.

Universal Serial Bus (USB) provides a serial bus standard for connecting devices, usually to computers such as PCs, but is also becoming commonplace on cameras.

VGA.

Video Graphics Array (VGA) is a computer display standard first marketed in 1987 by IBM

Verification

Activity providing qualitative assurance that a fabrication or assembly process was successfully completed.

Wide-angle Lens.

In photography and cinematography, a wide-angle lens is a lens whose focal length is shorter than the focal length of a normal lens.

X-rays.

A form of electromagnetic radiation with a wavelength in the range of 10 to 0.01 nanometers, corresponding to frequencies in the range 30 to 3000 PHz (1015 hertz). X-rays are primarily used for diagnostic medical and industrial imaging as well as crystallography. X-rays are a form of ionizing radiation and as such can be dangerous.

Zoom Lens.

A mechanical assembly of lenses whose focal length can be changed, as opposed to a prime lens, which has a fixed focal length.

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