# Camera as the Instrument: The Rising Trend of Vision Based Measurement

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Due to continuing and rapid advances of both hardware and software technologies in camera and computing systems, we continue to have access to cheaper, faster, higher quality, and smaller cameras and computing units. As a result, vision based methods consisting of image processing and computational intelligence can be implemented more easily and affordably than ever using a camera and its associated operations units. Among their various applications, such systems are also being used more and more by researchers and practitioners as generic instruments to measure and monitor physical phenomena. In this article, we take a look at this rising trend and how cameras and vision are being used for instrumentation and measurement, and we also cast a glance at the metrological gauntlet thrown down by vision-based instruments.

Instrumentation and Measurement (IM) as a field is primarily interested in measuring, detecting, monitoring, and recording a phenomenon referred to as the measurand and its associated calibration, uncertainty, tools, and applications. While many of these measurands are invisible to the human eye, for example the amount of electrical current in a wire, there are many others that can be seen visually, such as the number of people in a room. As such, it is intuitive to develop tools and methods that would *see* the measurand similar to the human eye and measure it. Such tools would be primarily electrical and/or electronic devices, possibly (though not necessarily) computer-based and would receive a picture of the scene from a camera or similar visual sensor, sometimes able to sense in a wider band of electromagnetic radiation (infrared, UV, X-ray, etc.) than processed by the human eye, and perform certain operations and or computational processes to measure or detect the subject of interest. In this article, we refer to such an (IM) approach as Vision-Based Measurement (VBM). Because it uses electronic devices and computers, VBM cannot only be automated but is also typically faster and more accurate than what the human eye can see and measure. In addition, since the main instrument is typically a camera plus associated operational or computational units, it is quite generic, affordable, and accessible by most researchers and practitioners, which has helped making VBM more ubiquitous and applicable.

The *IEEE Transactions on Instrumentation and Measurement* (TIM) has been publishing VBM papers since as far back as 1989 [1], possibly older depending on what experts agree to constitute *vision* in the context of those times. However, due to the recent hardware and software advances described at the beginning of this article, we are witnessing a significant increase in the number of VBM papers both submitted to and accepted by TIM in recent years. In fact, since 2009, TIM has published more VBM papers than it had in its history up to that point, indicating a rising trend for the present and the future of IM. This has served as motivation for us to write this article to promote VBM and introduce it to IM practitioners who are not already familiar with it.

## Current Trends and Applications

In the context of IM, VBM is being proposed and used today in a wide variety of automated applications and scenarios: counting the number of people in a building, for safety reasons, using existing surveillance cameras [2], detecting fire from video feeds of closed circuit cameras [3], camera-based vehicle instrumentation used to analyze the intentions and state of a driver (sleepy, yawning, not looking at the road ahead, etc.) and to detect potential driver errors before they happen to significantly reduce car accidents [4] and [5], and even counting the number of calories and the amount of nutrition in a meal simply by analyzing the image of the food [6]. An interesting observation about these applications is that, although they seem to be in very different and unrelated fields, they all use the same IM principle: analyzing a picture taken by a camera or visual sensor to measure or detect a phenomenon. The same principle also applies to biometric IM systems that detect the human face [7], and [8], iris [9], and [10], or fingerprint [11] and [12], as well as medical IM systems that detect, for example, skin problems such as dehydration or allergic reactions [13], and finally, gesture detecting instruments for human-computer interfaces [14] and [15]. Another really interesting possibility with VBM is when the camera captures the scene beyond what is visible to the human eye. For example, with an infrared camera, VBM can be used to measure the temperature of objects, such as steel production components that are otherwise very difficult to measure with other techniques [16].

The last example brings up a whole different domain of VBM usage. While most of the applications described above are relatively recent, VBM has been used for many years in factories and production facilities for inspection of equipment or products and detection of their properties, also known as no contact, non-invasive, or non-destructive inspection. The idea is again the same: a camera or visual sensor captures the subject of interest, and inspection is done by analyzing the captured data using hardware and/or software. This reduces production and operation costs by not only decreasing the manual labor that would otherwise be needed for inspection but also reducing the number of defects that could be missed due to human errors. This domain of VBM continues to develop today with many examples in automatic inspection:

- measurements of fabric texture characteristics such as weave repeat, yarn counts, and surface roughness [17],
- inspection of automotive rubber profiles which are difficult to process due to their complex shapes [18],
- lay length measurement of metallic wire ropes, which is an important dimensional quantity to pinpoint possible rope deformations and damages [19],
- three-dimensional coordinate measurement of a large-scale work piece, which is difficult in the mechanical industry and is needed to evaluate the assembling quality [20],
- defect detection in weld bead, which is important for high-quality welding [21],
- measurement of brake shoe thickness, which is a vital inspection of a train's braking system and is traditionally performed manually [22],
- detection of discrete surface defects in rail heads, which impact the riding quality and safety of a railway system [23], and
- detection of imperfections of a satin glass sheet as it is moving on a conveyor [24], to name a few.

Last but not least, the final group of VBM applications involve robot sensing and navigation to detect objects, obstacles, and paths [25], [26]. Such applications are used in a variety of industrial applications such as manufacturing as well as personal applications such as assistive robots for the elderly or the physically challenged.

As discussed, applications of VBM are indeed vast and far reaching in many sectors of industry and research: biomedical engineering, safety and security, vehicular technologies, transportation system, industrial inspection, human-computer interfaces, surveillance, assistive systems, and robotics, to name a few, and are becoming even more widely used due to increased affordability and capability of VBM hardware and software. To understand how VBM works, let us now take a look at it from a technical perspective.

## VBM Basics

The high-level architecture of a VBM system is shown in Fig. 1. At the hardware level, there are two main components: a visual sensor to capture an image, and an operations unit to process the image and *see* the subject of interest, together known as *vision*. It should be pointed out that the term vision is often used to refer to both *computer vision* and *machine vision*, which is correct since both are vision. In addition, the two terms are sometimes used interchangeably by practitioners, which is a common mistake. Though similar in many aspects, computer vision and machine vision are not the same when it comes to design, implementation, engineering, and applications. Traditionally, computer vision is mostly used in personal or daily-life applications and relies on computational methods running on computers or generic processor based systems, whereas machine vision is mostly used in industrial inspection or robotic applications and is typically implemented in dedicated hardware, sometimes without any computers or processor-based systems [27]. However, both of them use many common algorithms from image processing and computational intelligence, and both of them are used in VBM. So for the purposes of this article, we will not get into their differences, and our discussions are generic enough to apply to both. With this in mind, let us now present the details of the components depicted in Fig. 1.

## Visual Sensor

The visual sensor can be a visible-light camera, an infrared camera, a laser scanner, an x-ray scanner, or any other sensor that can obtain an image of the physical scene containing the measurand. Since the most commonly used visual sensor is visible-light camera such as a Complementary Metal–Oxide–Semiconductor (CMOS) or higher resolution Charge-Coupled Device (CCD), the captured image is most of the time very similar to a picture of the scene as seen by a human. For other types of sensors such as laser or x-ray, this image is different from what a human sees and is mostly meant for the consumption of the operations unit. Irrespective of the type of visual sensor, a key contributing factor to accurate measurements is the calibration of the camera and precise knowledge of its position, orientation, focal length, aspect ratio, principal point, distortion, etc. A variety of techniques are already available for camera calibration [28] and more are being proposed in recent research [29].

## Operations Unit

The operations unit receives the image acquired by the visual sensor and performs the necessary operations to obtain the desired measurements. This unit can be implemented in either software or hardware; i.e., it can either be programmed into a generic microprocessor based system such as the processing unit of a smart camera, or it can be implemented in dedicated hardware such as Field Programmable Gate Array (FPGA) or Application-Specific Integrated Circuit (ASIC). The unit itself consists of the following four major stages:

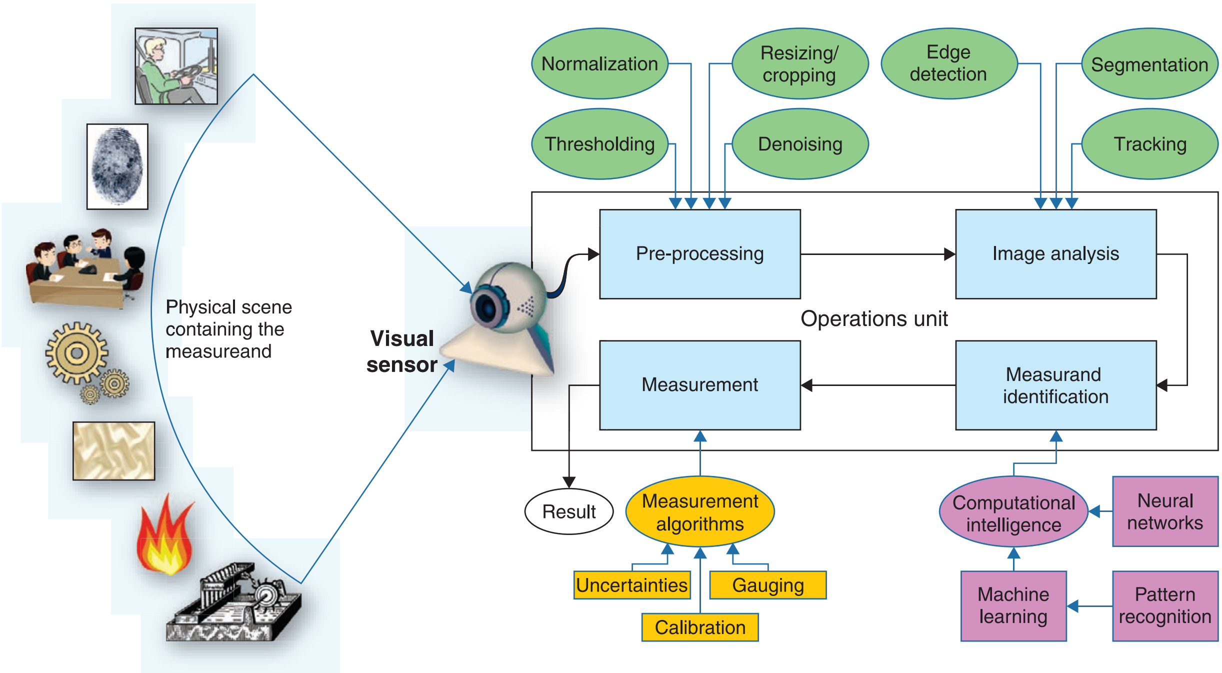


***Fig. 1.*** High-level architecture of vision-based measurement. Left to right: image is acquired by a *visual sensor* and is fed to the *operations unit* to perform image processing (green), computational intelligence (violet), and measurement operations (yellow).

- *Pre-Processing*: the purpose of this stage is to prepare the raw image for the next stage of operations. The image as acquired by the visual sensor could have deficiencies such as glare, noise, blurs, etc. In addition, it might not be in the form required by ensuing operations. For example, a fingerprint image is typically acquired in grey scale, but to be processed, it typically needs to be converted to pure black and white without any background. Pre-processing takes care of such needs and performs operations such as: normalization which modifies the pixel intensity and contrast of parts of the image, thresholding which converts the image into a binary black and white image, denoising which rids the image from additive white Gaussian noise or other types of noise, resizing, cropping, etc. These operations are signal processing, specifically image processing, with many methods and algorithms available for their implementation.
- *Image Analysis*: the purpose of this stage is to analyze the image and extract the necessary information for finding the measurand and doing the measurements later. This stage also uses image-processing operations, such as segmentation which divides the image into multiple segments each representing something meaningful in the scene, edge detection which finds the edges of objects in the scene and helps us identify objects of interest, tracking of objects after they have been detected and as they move through the scene, etc. For example, in Fig. 2 we can see color analysis and contour detection applied to food images so as to detect individual ingredients. At the end of the image analysis stage, the output is either the measurand itself or is information that can lead to the identification of the measurand. In the former case, we can skip the next stage, measurand identification, and move straight to the measurement stage. For example, to count the number of people in a room by counting the number of faces, once the faces have been detected in the image analysis stage, we can move straight to counting them without any further operations. However, in some applications, more operations are needed to identify the measurand. For example, as shown in the bottom row of Fig. 2, even though individual ingredients have been detected, we still do not know what they are exactly (apple? orange? bread? etc.). Hence, an additional identification stage is needed to answer this question. This stage is typically performed using computational intelligence operations, as discussed next.
- *Measurand Identification*: the purpose of this stage is to identify the specific measurand in the image, if it has not already been identified in the previous stage of image analysis. Techniques that are used here are mostly based on computational intelligence, especially machine

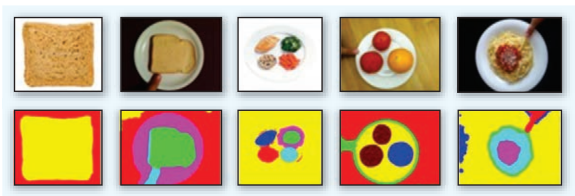

***Fig. 2.*** (top row) Food images as input to the image analysis stage and (bottom row) its output after performing color analysis and contour detection [6].

learning, and specifically pattern recognition and pattern matching, where the former provides a reasonable *most likely* matching of the given inputs to an output and hence introduces some uncertainties, while the latter looks for and reports exact matches of the given inputs to an *a priori* pattern. In this stage, we can find, match, and identify specific patterns, shapes, and classes of objects to identify our measurand. Optical character recognition and neural networks are also done at this stage if needed. For example, by feeding the bottom row of Fig. 2 into a Support Vector Machine engine that has been previously trained with similar food images in terms of color, texture, shape, and size, we can identify what ingredients exist in the food with a certain degree of accuracy. In some applications where the physical phenomenon only needs to be detected as opposed to gauged, such as gesture detection, our task is finished at this stage with the detection and identification of the measurand. On the other hand, in many other applications the measurand has to go through further measurement operations, as discussed next.

- *Measurement*: at this stage we have the measurand, and we can perform the required measurement operation such as gauging which gives us the dimensions of the measurand and its circumference, area, volume, etc., as well as temporal measurements when tracking the measurand and its state over time. An example of gauging is shown in Fig. 3, where the area of a single food ingredient that has been identified in the previous stage is determined. By assuming a more or less constant thickness of the ingredient, we can measure its volume from the area, use readily available food density tables to find the mass of the ingredient, and use nutritional tables to measure its calories and nutrition. Calibration is another requirement at this stage. In the above example, we need a reference to know the dimensions of the food ingredient, which in this case is the user's thumb (Fig. 3, right) that has been measured before and can be used for calibration here. As another example for temporal measurements, consider a driver monitoring application where, to detect yawning, we must first detect and track a closed mouth, then detect if the same mouth opens according to a certain pattern over a certain time, and then is closed again. The temporal relationship between the various states of the mouth is of utmost importance, otherwise there will be false positives because singing, or talking will be mistaken for yawning.

## Uncertainties and Their Sources

VBM systems, like every system employed for measurement purposes, can be considered actual measurement systems if they provide measurement results. The International Vocabulary of Metrology (VIM) [30] together with the Guide to the Expression of Uncertainty in Measurement (GUM) [31] represent the most important reference documents in metrology and define a measurement result, in clause 2.9, as a "*set of quantity values being attributed to a measurand together with any other available relevant information*."

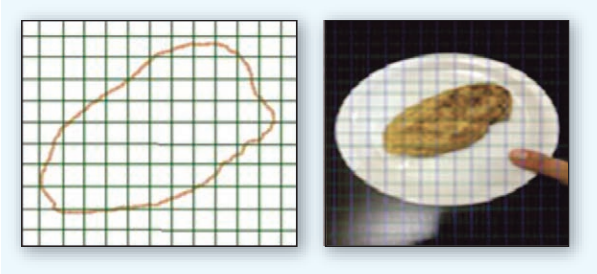

***Fig. 3.*** Food portion area measurement [6].

VIM also states, in note 1 about this definition, that

> A measurement result generally contains "*relevant information*" about the set of quantity values, such that some may be more representative of the measurand than others. This may be expressed in the form of a probabilitydensity function (PDF)."

In note 2 about the same definition, *A measurement result is generally expressed as a single measured quantity value and a* measurement uncertainty. Measurement uncertainty is hence an essential and necessary part of a measurement result, and according to the GUM [31], it is a "*parameter, associated with the result of a measurement that characterizes the dispersion of the values that could reasonably be attributed to the measurand.*"

To define this parameter, the GUM makes an important assumption in clause 3.2.4 [31]:

> *It is assumed that the result of a measurement has been corrected for all recognized significant systematic effects and that every effort has been made to identify such effects.*

Under this assumption, the only significant remaining effects are random, and consequently, the dispersion of values that could reasonably be attributed to the measurand can be represented by the standard deviation of a given, or assumed, PDF [32]. This standard deviation is called *standard uncertainty* and represents the fundamental stone on which measurement uncertainty is evaluated, also when the measurement result is not directly provided by a single instrument but is obtained as a combination of measurement results [32].

According to these concepts, to characterize a VBM system as a measuring instrument, it is imperative that the following steps are accomplished:

- All significant systematic effects shall be identified and recognized, and proper corrections shall be applied.
- The dispersion of values that could reasonably be attributed to the measurand shall be characterized in terms of standard uncertainty.
- If different parts of the instrument, including both hardware components and algorithms, are expected to contribute to the dispersion of values that could reasonably be attributed to the measurand, these two steps shall be repeated for all of them, and the individual obtained standard uncertainty values shall be suitably combined

[31], [32] to obtain the final, combined standard uncertainty associated to the measured value provided by the VBM system.

It is also imperative that the above steps are followed according to the GUM recommendations [31], since this is the only way to characterize the obtained measured values and compare them with measurement results obtained by instruments based on different measurement principles.

Specifically, as far as the VBM visual sensors are concerned, we can list the following main sources of uncertainties:

- *Lighting*: the lighting of the scene directly affects the values of the pixels of the resulting image, which affect the Image Processing parts in Fig. 1. Since the output of the image processing parts are input to the remaining parts, we can see that lighting conditions, in fact, affect the entire measurement system. Hence, applications in which the lighting conditions may vary are affected by this parameter. Lighting conditions can be seen either as systematic effects (for instance the presence of shadows is a systematic effect if they do not change during the whole measurement process) and random effects (for instance due to short term fluctuations of the lighting conditions). Both effects shall be taken into account when evaluating uncertainty.
- *Camera angle*: the angle with which the image is taken is also important in applications where the camera has a free angle and is not fixed, since the angle directly affects the shape and position of the measurand in the image. In this case, a systematic effect shall be considered and compensated for (due to the camera position), and the random effects shall be also considered, related to fluctuations of the camera position due to imperfections of the camera bearing system, vibrations, etc.
- *Camera equipment*: different cameras have different lenses, hardware, and software components, all affecting the resulting image taken with that camera. Hence, an application that is not using a specific and predefined camera can be affected by this parameter. Again, this may cause systematic effects as well as random effects and both shall be carefully considered.

There are also other uncertainties introduced in the particular image processing or computational intelligence algorithms used in the VBM system which must also be taken into account. As an example, denoising algorithms are not 100% efficient, and some noise is still present in the output image. This noise represents a contribution to uncertainty, so it has to be evaluated and combined with other contributions to define the uncertainty associated with the final measurement result.

When identifying and evaluating all individual contributions to uncertainty, it is also essential to compare different possible architectures (hardware and software) and understand which one provides the best performance, from the metrological perspective, under the different possible measurement conditions. This can be efficiently done only if well-established standards and techniques [31] are used.

## VBM Papers in TIM

The previous sections should have clarified what is needed to consider and characterize a VBM system as a measurement system. It is also very important for the VBM community to understand when a work in this field belongs mainly to pure image processing or pattern recognition fields and when it can be considered in the IM field.

Let us consider TIM as a significant IM venue to which, as already stated above, VBM papers are submitted and published regularly. TIM's scope has been defined to encompass research papers

> *that address innovative solutions to the development and use of electrical and electronic instruments and equipment to measure, monitor and/or record physical phenomena for the purpose of advancing measurement science, methods, functionality, and applications*.

A paper submitted to TIM must therefore clearly show how it satisfies the above requirements and must cover the related recent literature in the field of IM and position its own contribution with respect to the literature and compare itself either analytically or experimentally with existing methods, techniques, and applications in the field of IM. While we certainly encourage submission of VBM papers to TIM, we do not consider papers whose core contribution is strictly in vision, image processing, pattern recognition, or machine learning without any clear IM and VBM context. For example, a paper that proposes a more efficient image denoising technique or a faster edge detection algorithm without any direct IM context and without characterizing the proposed algorithm in terms of measurement uncertainty in a GUM compliant way, will not be considered at TIM. While both image denoising and edge detection could be of great use in VBM, they are too generic and can be applied to any other image processing and pattern recognition application as well, not just VBM. Hence, at TIM we redirect such papers to more appropriate journals such as *IEEE Transactions on Image Processing* or *IEEE Transactions on Pattern Analysis and Machine Intelligence*. Contrarily, a paper that proposes an image denoising or edge detection algorithm and then shows experimentally that the proposed algorithm can be used to count the number of people in a room or detect fingerprints more accurately than existing algorithms will be considered at TIM. While there is a lot of work in the field of vision, from an IM perspective, the evaluation of uncertainty and not just the definition of new algorithms is important. Any new algorithm becomes useful if and only if it brings increased accuracy or increased computational efficiency with the same accuracy.

## Conclusion

In this article we gave an overview of vision-based measurement (VBM), its various components, and uncertainty in the correct IM metrological perspective. VBM is a fast rising technology due to the increasing affordability and capability of camera and computing hardware/software. While originally a specialized application, VBM is expected to become more ubiquitous in our everyday lives as apparent from the applications described in this article.

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