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COLLABORATIVE HUMAN-MACHINE QUALITY CONTROL SYSTEM

STEPS TOWARDS AUTOMATIC MACHINE VISION INSPECTION

ANA EDUARDA DE SÁ SILVA
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Collaborative human-machine quality control system: steps towards automatic machine vision inspection

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Abstract

This thesis explores ways of increasing the efficiency of an industrial process by resorting to automated machine vision technologies. The research focuses on the quality inspection process in the tire industry.

The general trend found in the literature to improve the efficiency of quality inspection processes is to introduce machine vision systems to replace humans in the visual search and conformity decision tasks. The original contribution of this study is showing that operators should be integrated in the development process and perform continuous validation of each technological sub-component. In such an ambiguous and complex task as quality inspection process of tires, operators' expertise and knowledge needs to be acquired to assure that the technological solutions being proposed sustain the same quality standards. Thus, the machine vision solutions developed during this research project do not aim at replacing the operators, but rather at maximizing the advantages they bring to the inspection system through a Computer Assisted Inspection (CAI). This will continue up to a moment in which technology reliability is demonstrated as adequate and the automated solutions can be deployed as a stand-alone inspection method.

The thesis is based on qualitative and quantitative research undertaken over three years in collaboration with Continental Mabor SA. Initial chapters explore the current inspection methods used by specialized operators. Later chapters describe the underlying concepts and the re-design process of the inspection system. This proposed process follows a framework that considers scenarios of different levels of automation. A prototype suitable for industrial environment was developed and made possible proving the validity of the proposed solution. Each sub-component of the system was tested and validated through systematic experimentation. Special focus was given to the image-acquisition station, as the appropriateness of the images influences both human-based and automatic subsequent quality assessments.

In the chapters focused on the results it is shown that combining operators' knowledge, machine vision technologies and automatic detection algorithms contribute to an increase in process efficiency (higher throughput) and effectiveness (increase the number of correct decisions). The baseline strategy for automatic imperfection detection based on a self-adaptive and deformable template match (SAD-TM) technique is proposed in this dissertation and validated for a number of cases. Future work should focus on the continuous development of automatic detection algorithms, enlarging number of imperfections tested and refining its detection capabilities.

The main outcome of this thesis is the development on the understanding of the potential benefits of introducing machine vision technologies in the quality inspection process of tires. The proposed strategy of complementing human and automation towards the development of more efficient processes is expected to be applicable in other environments besides the tire industry.

Regarding the outcomes that are relevant to the industrial partner, the performed research suggests that the industrial implementation of the proposed system is viable and should occur iteratively, attempting to a continuous increase of level of automation.

Resumo

A tese apresentada explora formas de aumentar a eficiência de um processo industrial recorrendo a visão por computador. A investigação centra-se no processo de controlo de qualidade na indústria de pneus.

A tendência dominante encontrada na literatura, no que toca à melhoria da eficiência do controlo da qualidade, consiste na introdução de sistemas de visão por computador em substituição de operadores. A contribuição mais inovadora deste estudo é demonstrar que os operadores devem ser integrados no processo de desenvolvimento e que os subcomponentes tecnológicos devem ser sempre validados juntos destes. No caso de uma tarefa tão ambígua e complexa como a inspecção de qualidade de pneus, as suas competências e conhecimentos devem ser captados de forma a assegurar que a solução tecnológica apresentada é capaz de garantir os mesmos níveis de qualidade. Desta forma, as soluções que envolvem visão por computador e que foram desenvolvidas durante este projecto de investigação não tencionam substituir os operadores, mas antes maximizar as vantagens que estes trazem às tarefas de inspecção num meio assistido informaticamente. Esta situação deverá manter-se até que a tecnologia demonstre uma fiabilidade adequada e as soluções automatizadas possam ser implementadas com um método de inspecção autónomo.

A tese baseia-se em investigação qualitativa e quantitativa que decorreu ao longo de três anos em colaboração com a Continental Mabor SA. Os capítulos iniciais exploram os métodos de inspecção actuais utilizados por operadores especializados. Os capítulos conseguintes descrevem os conceitos subjacentes a um sistema de inspecção e o seu processo de desenvolvimento. Ao longo deste processo são ponderados cenários com diferentes níveis de automação. Cada subcomponente do sistema foi testado e validado através de experimentação sistemática. Especial destaque foi dado ao sistema de aquisição de imagens, dado que a adequação das imagens influencia tanto a inspecção feita pelos operadores, como as avaliações automáticas subsequentes.

Nos capítulos focados em resultados mostra-se que a combinação de conhecimentos detidos pelos operadores, visão por computador e algoritmos de detecção contribuem para uma maior eficiência do processo (*throughput* mais elevado) e efectividade (maior número de decisões correctas). A estratégia para a automação da detecção automática de imperfeições baseada numa técnica de *template match* auto-adaptativa e deformável é proposta nesta dissertação e validada para um conjunto de casos. O trabalho futuro deverá incidir principalmente no desenvolvimento continuado de algoritmos de detecção automática, aumentando o número de imperfeições testadas e refinando as suas capacidades de detecção.

O principal resultado desta tese é o desenvolvimento no sentido de compreender os potenciais benefícios da introdução de tecnologias de visão por computador na inspecção de qualidade de pneus. A estratégia proposta de complementar reciprocamente os contributos trazidos pela automação e pelos operadores com vista a um processo mais eficiente tem perspectivas de aplicabilidade em outras indústrias para além da indústria de pneus.

Ao parceiro industrial, esta investigação sugere que a implementação do sistema proposto à escala industrial é viável e deve ocorrer iterativamente, com vista a um aumento contínuo do nível de automação.

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List of Acronyms

2D	Two-dimensional
3D	Three-dimensional
CAD	Computer-Aided Design
CAI	Computer Assisted Inspection
CCD	Charge-coupled device
DOT	Department of Transportation
FOV	Field of View
fps	Frames per second
HSL	Hue, Saturation, and Lightness color model
LED	Light-emitting diode
LOA	Level of Automation
NC	Non-conformity
NOK	Not Okay
OpenCV	Open Source Computer Vision Library
OpenGL	Open Graphics Library
PCB	Printed Circuit Board
PWM	Pulse-width Modulation
px	Pixel
RGB	Red, Green, and Blue color model
SAD-TM	Self-Adaptive and Deformable Template Match
SKR	Skill-Rule-Knowledge
TM	Template Matching
WSH	Window Search Height
WSR	Window Search Radius
WSW	Window Search Width

List of Symbols

ω	Angular speed
R_c	Camera vertical resolution
f	Focal length
G	Gain
E	Illuminance
I	Intensity
v	Linear speed
M	Magnification
R_s	Spatial resolution

There's nothing you can know that isn't known.
Nothing you can see that isn't shown.
Nowhere you can be that isn't where you're meant to be.

Lennon–McCartney
All You Need Is Love

Chapter 1
Introduction

Visual inspection in a manufacturing system is described as the process to separate defective products from defect-free products (Drury 2001). The criteria to distinguish between both situations may be from two origins: functional or aesthetics. When done manually, visual quality inspection can be a very monotonous and exhausting task, which can cause fatigue, stress and lead to subjective decision processes. The objective of this dissertation is to re-design an inspection process and understand if the introduction of automated aids can contribute to an increase in its efficiency (higher throughput) and effectiveness (increase the number of correct decisions). The process of manual tires inspection was the industrial case in the basis of this research for which this hypothesis was tested and validated.

1.1 The nature of manual visual inspection

In the literature, the effectiveness of human visual quality inspection is estimated to lay around 80% (Sannen and Van Brussel 2009). This means that there is a significant probability that the quality assessment of one operator is not in agreement with the assessment of another operator. This fact contributed to the general belief that humans are less reliable and less consistent compared to automatic systems (Laofor and Peansupap 2012; Malamasa et al. 2003). On the other hand, there might be essential components in the inspection processes that greatly benefit from human intelligence and how they act accordingly to the know-how acquired through different levels of experience and trainings. Tire inspection is nowadays a human-based industrial process and an example of a process in which the subjectivity of the quality criteria demand highly trained and qualified operators. In fact, inspecting a tire is a complex manual process in which one single inspector collects and analyzes multiple characteristics of a tire. The perception and action-related processes during manual inspection are overlapping in space and time and the operators are confronted with multiple sources of information. The output of the operators' analysis leads to a decision of whether the tire is OK or NOK. When the operator detects an imperfection, he has to decide if it is critical or not and, in this last scenario, separate the product from the production flow (Baudet, Maire and Pillet 2013). The variables that influence the operator decision include aspects such as: tire visual appearance, intensity of the imperfection, tire article and its costumer, the historical quality data of that tire, operators' fatigue and situation awareness, operators' level of experience, etc. Moreover the ambiguity and variability of imperfections that can occur in tires demands that highly skilled operators are trained to perform quality inspection. On the other hand, the fact that it is a human-based process, adds to the inspecting process some natural variability in terms of methods of detection, quality criteria and productivity. Standardization of the procedure is difficult to achieve and so is the calibration of criteria between different operators and even regarding one operator when exposed to different conditions.

This thesis was motivated by the need to increase the efficiency of the quality inspection process of tires. Automotive tire manufacturing is a highly competitive industry, in which 70% of revenue was generated by top ten manufactures in 2010 (ETRMA 2011). To maintain or increase its competiveness, every manufacturer is looking for strategies to reduce costs and gain productivity. The manufacturing plants are being upgraded with cutting-edge technologies and automated systems with the objective of continuously improve the production efficiency while maintaining quality standards.

In the tire industry, manual quality inspection of tires is part of the Quality Control. Besides the implementation of practices to prevent imperfections from happening along the process, the final quality control exists and is the last process step before the tire is stored and shipped to the costumer. Although the main direction of Quality Control is to define strategies to produce defect-free tires, the fact that the manufacturing process involves many different steps and several different and unstable raw materials, raises the need for a final quality inspection. There are many variables in the manufacturing process that can originate an imperfection in a tire, some of them known and possibly controlled (operator that misplaced a part in the assembly process) and others which effect is unpredictable (room temperature, humidity, etc.). The unavoidable inaccuracy of the manufacturing process, together with the fact that the tire is a critical safety item in a car, leads to the existence of a final quality inspection at the final stage of the production process. Although typically described as a non-added value process, final inspection is critical to guarantee that the tire is delivered to the customer within the quality criteria. Especially for the tire manufacturers' leaders, delivering products with high quality is essential to sustain sales and market share. In this market, the cost to deliver a product extends beyond the production cost and aspects such as customer support and claims need to be taken into account. Moreover, for being a safety item, customers have low tolerance for tires that are delivered outside the specifications. For this reason, and to enhance competitiveness, the inspection process of tires, at least in the main manufacturers, is done manually to all parts produced.

Questioning the need of final inspection is not the target of this dissertation. Rather the objective is, by assuming the existence of a final inspection process, re-design it and evaluate the gain in efficiency achieved by introducing some automatic components. Furthermore, improving the final inspection process is totally compatible with the trend of building quality into the process upstream (Tan, Handfield and Krause 1998). Although important emphasis is being given to defect prevention, these efforts in the tire industry still do not preclude the need of final inspection and so it will be in the foreseen future. For this reason, tire manufactures are continuously looking forward to possible improvements in the final inspection process that can lead to cost reduction.

In the last two decades, machine vision technologies have been increasingly used in the development of automatic systems in many different industrial applications. The continuous advances in high-speed and high-resolution vision technologies simultaneously with improvements in robotics enlarge the possible applications. That also happens in the tire industry, where vision technologies are being deployed for inspection and traceability tasks over the entire production cycle (for example tire-tread dimensional check after extrusion). Despite all the efforts and technological advances, a vision system able to automatically perform the aesthetic and functional final inspection done by the operators was not yet developed. The variety of imperfections that can occur and the complexity of determining its severity still demand human intervention to take the pass/fail decision. This complexity does not eliminate *per se* the possible improvements of introducing vision and automated technologies, rather it raises the challenge on how should the process be re-designed so that automatic components and human intervention are placed together with the target of maximizing the efficiency of the final inspection process. The continuous development of a collaborative system that evolves with time, has the potential to, one day, originate a fully automated inspection process.

The approach followed in this research is to first perform a detailed analysis of the current final inspection process of tires and later analyze if some technological aids, namely machine vision technologies, can improve the throughput and move it towards a more efficient process. The objective is to re-design the inspection process and determine which steps of the inspection process could be automated and define if some (and which) should remain allocated to the operators.

1.2 Automated and hybrid manufacturing systems

Automatic manufacturing systems are undergoing a rapid growth in a broad range of applications. Automation can offer many advantages, such as an increased productivity and elimination of some human errors. Even though, some studies suggest that while automation has eliminated some types of operators' errors, it has also created the potential for new types of problems (Leveson and Palmer 1997). By late 1980s and early 1990s, it was generally accepted that the demand for manufactured goods would be met by a small workforce operating a highly modern organization employing productive and automated technologies (Bargelis, Hoehne and Cesbulevicius 2004). It was frequently argued at this stage that humans were error prone and thus it was necessary to limit their influence in manufacturing by using automated technologies (Mital 1997). There are some functions in which automation can indeed provide potential advantages when the human functions are transferred to automatic systems. But the reality is that fully automated processes are only viable in limited circumstances, either due to technical or economic reasons. When feasible, fully automated systems frequently allow minimization of lead-time but also limited flexibility and for this reason they are typically dedicated to single products (Dencker et al. 2009).

The conscious that rarely ful automation allows companies to meet necessary market requirements of flexibility and cost efficiency, forced the development of other possibilities. More recently some research groups identified hybrid systems (semi-automated systems) as benefic for industrial environments in scenarios in which the market demands vary significantly or in cases there is a high variety of products which requires production flexibility. In a hybrid system, there is a close linkage of human and automation in cooperative tasks that when properly designed use the strengths of both sides. Sheridan (1995) elaborates about this type of hybrid automation as the process of "allocate to the human the tasks best suited to the human, allocate to the automation tasks best suited to it" and in that way "achieve the best combination of human and automatic control, where best is defined by explicit system objectives".

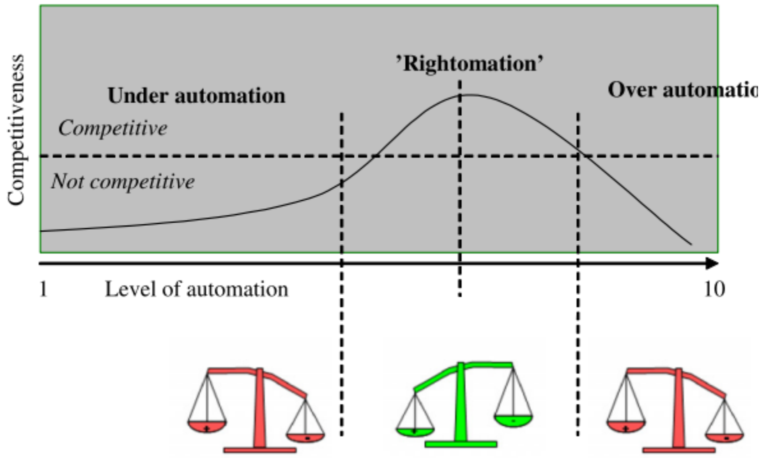
In the literature there are a significant number of studies analyzing the performance and benefits of hybrid assembly lines over manual or fully automated ones (Krüger, Lien and Verl 2009; Takata and Hirano 2011; Consiglio, Seliger and Weinert 2007). The concept of hybrid systems has also gained acceptance in the research and industrial communities when some studies reported that many conventional automated lines had recently been replaced by hybrid lines or cells, with improved outcomes (Takata and Hirano 2011). Typically the automatic component of these systems is a robot that is associated to load tasks aiming at reducing heavy handling tasks from operators. Handling and positioning of heavy parts in welding and assembly processes have been described as examples of tasks transferable to machinery (Busch et al. 2012). In these cases, the human-robot cooperation combines the sensory skill, the knowledge and the skillfulness of the worker with the strength and speed abilities of the robot (Schraft et al. 2005). Besides the usage of robotics to automate some physical intensive tasks, other automation technologies are being used to support human tasks. As a matter of fact, automation will be assumed along this document as a broad range of technological systems designed to support human operators during task performance (Cuevas et al. 2007). As an example, there is a strong research and development area towards intelligent decision-support aids to help aviation pilots. Today pilots control the aircraft indirectly through instructions to the automation in a more passive and supervisor manner. Also in the medical field, physicians are improving their perceptual-motor capabilities by using computer vision and robotic assisted instruments (Lee et al. 2010).

In brief, as robotic systems have become more complex and major advances have been done in other technological areas such as sensor integration, complex and intelligent machine vision systems and sophisticated mathematical algorithms, the cooperation between human and automation has moved from simple physical work load reduction to more "joint cognitive systems" (Hoc 2000). Models to define tasks, dynamically decomposed it into subtasks, and distribute them among human and automation agents are extensively discussed in the literature.

The role of the operators in these hybrid systems also changed with the introduction of new system principles and technologies. Operators are now expected to behave agile and proactively, rather than just executing simple and repetitive tasks (Dencker et al. 2009). As stated by Parasurman and Riley (1997) "automation does not supplant human activity; rather, it changes the nature of the work that humans do". Without the right operator task association and knowledge level, automation cannot be utilized to its full extent. Many studies underline the importance of correctly define and structure the human involvement in the hybrid systems. In addition to extreme situations, where the human operator takes full manual control of the system (no automation) and in the ones where there is no human intervention (full automation), many intermediate levels of automation (LOA) can be considered (Kaber, Onal and Endsley 2000; Kaber 2004).

Many models and studies have been published aiming at determining the level of automation that best suits the needs and requirements of the environment in which the automated equipment will be used. The interaction between human operators and advanced automation technology can sometimes became highly complex and psychological, cognitive, social, and technological aspects need to be accounted for (Cuevas et al. 2007). The use of intermediate LOA as a way of improving human-automation performance has been proposed in many studies (Kaber, Onal and Endsley 2000; Kaber 2004; Fasth and Stahre 2008). Säfsten, Winroth and Stahre (2007) went even further in categorizing intermediate LOA and suggested the existence of ‘under automation’, ‘over automation’ and ‘rightomation’. The first two can have negative effects on manufacturing performance while ‘rightomation’ contributes positively in several respects (Figure 1.1).

Despite these studies and evidences, some technology experts continue to favor a technology-centered design of automation. In fact, the advocates of automation continuously report approaches towards higher levels of automation (Miller and Parasuraman 2007). The decision of whether or not ful automation is preferable depends significantly on the task complexity and available technological solutions. Even when achievable, the system designer has to consider that inevitably, situations in which automation cannot handle will arise. In these circumstances, operators are expected to step in and resolve the situation. In case the operators have been “out of the loop” and replaced by automation, their ability to do so may be impaired (Harrison, Johnson and Wright 2003). The view of human-centered automation is to keep operators “in the loop” and to view automation as assisting tools even if human interference is minimal or tends to decrease with time and continuous technological advances. Not considering human intervention while re-designing systems may induce losses in situation awareness and human knowledge degradation which may disable their ability to take appropriate corrective actions when needed (Parasuraman and Manzey 2010).



Examples of effects	Ergonomics	- -	+ +	-
	Efficiency	-	+ +	-
	Productivity	- -	+ +	+ +
	Quality	-	+	+ +
	Lead time	-	+	-
	Delivery precision	-	+	-
	Up-time	+ +	+	-
	Competence	+	+	-
	Investment cost	+ +	+	- -
	Capacity	-	+	+ +
	Maintenance	+ +	+	- -
	Sum	*7 + / 9 -*	*14 + / 0 -*	*7 + / 10 -*

Figure 1.1 - Appropriate level of automation, ‘rigthomation’, and positive and negative effects of ‘under automation’ and ‘over automation’ (Säfsten, Winroth and Stahre 2007).

This dissertation suggests that the design of collaborative systems between operators and automation can also be positive in other manufacturing processes rather than assembly and material handling, such as inspection process. There are many studies suggesting the use of fully automated systems for quality inspection by means of computer vision technologies. Industries such as PCB manufacturing, welding, food products, amongst others, are currently using fully automated computer vision solutions (Brosnan and Sun 2002; Moganti et al. 1996). In these examples, automated vision systems are routinely being used for the purpose of performing measurements, integrity checking, and quality aesthetics control. On the other hand, humans are currently known for being very good at inspection tasks for short periods of time. The human vision system can adapt to varying lighting conditions and easily ignore irrelevant information (Killing 2006). This means that in cases the decision process is very complex, coupling strategies may become attractive. Tire inspection may be one of these examples. A human process that encompasses significant individual differences in perception, knowledge, and judgment cannot trivially be transferred to technological solutions and mathematical rules.

1.3 Research gap and research questions

Tire quality inspection is a complex manual manufacturing process step. As every manufacturing process, perfect inspection is not possible to be obtained at all levels and for all participants. Nevertheless the extensive knowledge and training given to the specialized operators allows for impressive performances either in visual search of the nonconformities (NCs) and in the subsequent decision making process (rejecting or accepting the product). In the context of tire manufacturing process, final inspectors play a significant role in the reputation of the company (by avoiding defective products to be delivered to customers) but also in the throughput of the manufacturing process (by avoiding rejecting acceptable products). Besides the inherent complexity of localizing NCs in a rotating black object with black indents, framing the visual detection in the quality criteria is sometimes even more difficult. The acceptable quality level of a product is, as mentioned by the inspectors, a "grey area and many different interpretations are possible".

Improving the efficiency of the quality inspection of tires is the main objective of this dissertation and to do so many different approaches could have been followed. An attempt to fully automate the quality inspection process was the initial strategy suggested by the top management of the industrial partner. Without putting that possibility aside, the first step taken was rather to obtain a deep understanding of the industrial and scientific context of this problem.

There is a significant number of NCs that can occur in a tire, each of them can impact the aesthetics and/or functional conditions of the product. Vision is the main sensorial source of information although haptic capabilities are sometimes used by the operators for a better evaluation. For being mainly a visual inspection problem, many machine vision companies have attempted to address the problem through the combination of high-quality cameras (for image acquisition) and image processing techniques (for automatic detection of NCs) towards the development of an automatic inspection system (Mueller 2013). Due to the fact that the variety of NCs is very high (in shape, appearance and size) and the decision process very complex, there is, to the best of my knowledge, no commercial automatic machine vision solution able to mimic the inspection done by the operators and to assure the quality standards. In these attempts, the question was if full automation was possible or not and the appropriateness of different levels of automation seems not to have been treated. Regardless of these limitations, tire industry is already taking advantage of the most recent advances in vision and automation technologies mainly for automatic geometrical measurements for both in-process monitoring and final product verifications. Laser-based vision sensors are the most common vision technology in tire manufacturing operations and the recent developments in sensor speed and resolution allowed for successful industrial implementations in replacement of capacitance sensors (Pastorius and Snow 2006). For geometry and profile measurements, non-contact laser scan seems to be the most adequate technology for not being significantly affected by changes in surface appearance, such as color, finishing, or lubricants (Frosio et al. 2011).

In the scientific context, a literature search for ‘‘automatic + tire + inspection’’ within peer-reviewed literature did not retrieve a significant number of results. The very few publications found were focused in evaluating the performance of machine vision technologies when applied to tires. Incipient studies in laboratorial conditions suggesting laser scanners, thermal cameras, shearography and non-destructive x-ray were found (Gee et al. 2000; Frosio et al. 2011; Kim et al. 2004; Gray, Dumont and Abidi 1999). The scarcity of scientific literature in the field suggests that major advances are more related with incremental improvements in vision sensors specifications. These typically occur among machine vision manufacturers.

Tire manufacturing process is far from being a 100% defect–free production and this is mainly due to the nature of the material in use. Unlike metal parts for example, rubber materials, even when within tolerances, are influenced by temperature, moisture, etc. Machine vision systems’ manufacturers consider this as an opportunity to go upstream in the production process and implement automatic vision quality system in each production step (Wordsworth 2011, 2008). The fact that there are machine vision manufacturers whose main industrial applications are dedicated to tire industry gives a notion of the importance of the market and the acceptance of the industry which does not want to lag behind other automotive industries when it comes to increase efficiency and quality in the processes.

Final inspection of tires is not unattended by the machine vision manufacturers but the complexity of the problem reduces the chances that a single manufacture develops the needed technology together with the adequate systems’ design.

The literature described in the previous section in the scientific domain of cooperation between humans and automation, suggests that there are advantages in integrating humans and automation when re-designing manual processes. Although not directly applied to the tire industry, some studies highlight some drawbacks of implementing automatic solutions without considering the role of the human operator or simply assigning to the operator the tasks that for some reason cannot be automated. Taking this research trend into consideration, the concept of a Computer Assisted Inspection (CAI) was created. The novel contribution of this dissertation lies on the development of a concept of a self-sustainable inspection process that merges the information acquired from automatic vision sensors with human and automatic decision capabilities. Self-sustainable in this context means the capability of adjusting throughout time and, based on statistical and historical data analysis, the level of automatic and human-based decisions according to advances in image processing techniques, changes in product specifications or costumer requirements. Unlike many studies in which the LOA is decided in the designing phases of a process and remains steady from that point on, this research suggests that there should be a continuous re-evaluation of the system performance, based on which the level of trust in automation could increase or decrease. The objective of this dissertation is to demonstrate that the re-designing of the inspection systems allows for a significant improvement in its throughput and leads to a more flexible and reactive process able to provide a better traceability of the quality in the production process.

In this concept the inspection process will be subdivided in sub-systems. What was before a hands-on one-to-one relation between one inspector and one tire will now be a process decomposed in acquisition station, image processing algorithms and CAI. These technological sub-systems will be mentioned as assistive technology. In brief, the acquisition station is a mechanical system that combines vision sensors and lighting used to scan all surfaces of the tire with high-resolution digital cameras. By means of image processing techniques, potential defective areas in the tire are detected. Finally, the operators analyze the potential defective areas in the images and assign a final decision according to the defined quality standards.

The human-based CAI of tires will play different roles in each of the phases of this work. These phases are: development, validation phases and plan for industrialization. In the development phase the CAI allows, in one hand, the validation of the image quality by the most knowledgeable agents (human inspectors) and, on the other hand, the storage of human-based decisions. These decisions can then be used to develop automatic detection algorithms. In the validation process the decisions made by the operators using the CAI can be compared to the ones obtained by the automatic detection algorithms. Finally, when implemented, this strategy is hypothesized to allow a continuous optimization of the overall inspection time of a tire. In the early-stage of implementation the algorithms may not be able to distinguish the non-conformities from many other irrelevant artifacts but can already detect defect-free tire regions. In this scenario, CAI is performed by operators that digitally analyze only the regions in which the algorithms could not take a conclusive decision. Step by step the classification capabilities of the algorithms may increase and the regions shown to operators are successively lower. The overall concept of a CAI is not to avoid and replace the human operators in the inspection process but rather to develop a tool to assist them in taking more assertive and fast decisions. Progressively concentrate the operators in the ambiguous pass-fail choices and provide them adequate tools to do so is believed to have a significant positive impact in the process efficiency. A collaborative decision between operators and automation may contribute to an improved performance level of the process. If in the future the algorithms become reliable enough to perform inspection without the need of operators validation. The inspection process might one day become 100% automatic. Although this stage of full automation was not achieved along this dissertation, a suggestion for a continuous implementation is presented and the work here described is an essential step to allow this.

This system will considerably change the methods and procedures of quality inspection of tires. The operators will assess tires' quality level digitally instead of looking at the physical object. The development of this CAI aims at reducing inspection time and operator physical workload while promoting an improvement in quality performance level. From the inspection point of view, the minimum requirement is that the same (if not better) detection rate is achieved. From the process point of view, the new process aims at improving throughput while reducing operators' stress and fatigue. However, a methodology for development and implementation phases needs to be carefully designed. The expected benefits of the CAI may be compromised if aspects such as adequate training of operators for the new environment and accounting for the learning period are not considered.

In sum, the topics covered along this dissertation enclose multidisciplinary technical and systems thinking research. The same level of importance is given to the technological aspects implied in the development of the new system, as well as to the process of integrating the developed technology and human operators towards the development of more effective manufacturing process. The relevance of this research is intended to go beyond the application to the tire industry and provide new hints to the design of self-sustainable hybrid manufacturing systems. Even though, inevitably there will be research specifically oriented to a successful development for the case study of tire inspection.

The defined research approach will hopefully help answering the research question described in Figure 1.2. To precisely answer this question, several aspects of the new system need to be investigated and each step of the new system needs to be properly validated. For this reason, multiple sub-questions were formulated to help further structuring the research done.

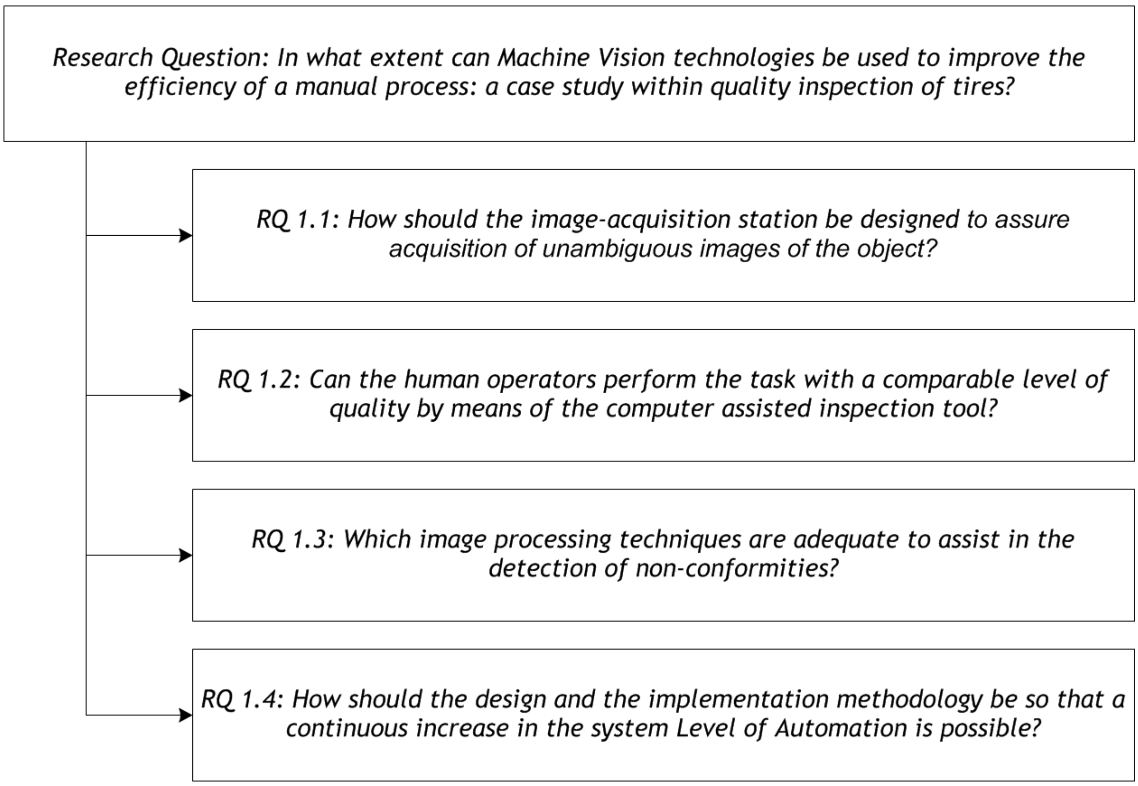


Figure 1.2 – Main research question and subsequent division in sub-questions.

The first two research-questions are characteristically technical and the appropriateness of off the shelf vision sensors in the acquisition of tires' image is one of the topics to be studied. Special attention will also be given to the placement of the cameras and lighting system, which can determine the effectiveness of the subsequent quality detection. Highlighting the defects and fading the standard tire lettering and embossments would be advantageous for both automatic and human-based inspections. An iterative validation process in collaboration with the human operators was defined to identify the most suitable camera-lighting set-up which may differ among different products (RQ 1.1 in Figure 1.3).

A set of experiments was performed with the participation of the operators to evaluate the effectiveness of CAI. A posttest-only controlled trial was designed to compare the performance of operators using CAI tools with the current process (RQ 1.2 in Figure 1.3). The participation of the operators in this validation process was essential to conclude about possible benefits of the CAI. Also, the fact that the operators felt involved in the process of re-designing the inspection system favored the development of improvements based on their experiences and suggestions.

The research done in attempt to answer RQ 1.3 is probably the one more oriented to the tire application. The fact that the tire is a black object with low contrast, forces the development and the use of image processing techniques that are able to discretize small differences in intensity. Furthermore, the approach followed to automatically detect defective regions is based on an adaptive matching procedure in which the images of the tire that need to be assessed are compared with defective-free images of the same product. A straightforward image processing technique as template matching turns out to be complex when applied to tires because of the low contrast but also because of the flexibility of the object, which originates differences that need to be neglected among products.

Finally, the results obtained along the development steps allows for the definition of a methodology for a continuous implementation of this system (RQ 1.4 in Figure 1.3).

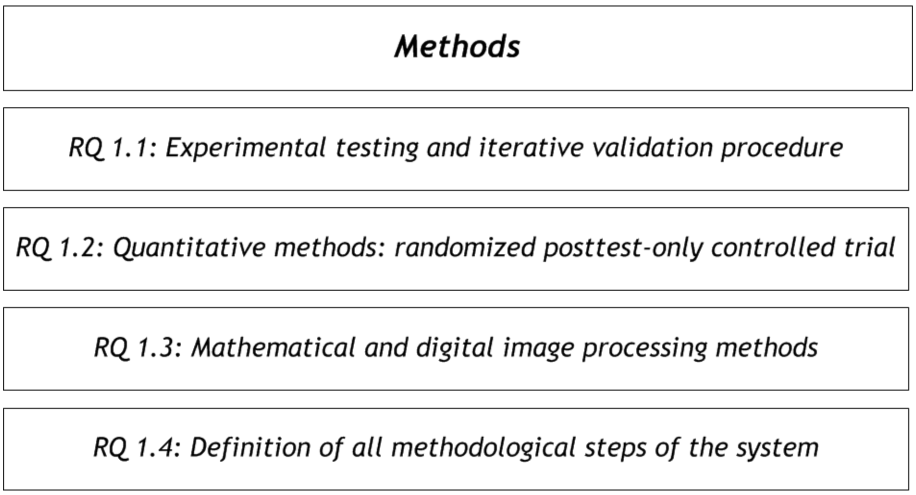


Figure 1.3 – Methods used to answer each sub-research question.

1.4 Research institutions and industrial partner

The present investigation was possible due to the interaction between different research institutions together with a strong industrial collaboration. Each organization dedicated time and human resources to this project which enabled the creation of a multidisciplinary team. The research described along this document is mostly an individual contribution extracted from a project that covered many other topics than are not mentioned in this document for being responsibility of other colleagues. The institutions involved in this research were:

Faculty of Engineering of University of Porto (FEUP) and INESC TEC

Where the project was based and a significant part of the investigation was done. Through the Robotics and Intelligent Systems Unit, access to advanced know-how in automation, vision systems and image processing techniques was possible.

University of Minho

To complement the expertise from FEUP, members from the Department of Industrial Electronics participated and provided guidance to this research.

Massachusetts Institute of Technology (MIT)

Sharing experiences and exchanging ideas with researchers from the Engineering Systems Division at MIT reinforced the importance of analyzing the engineering and technological challenge considering the surrounding social and organizational context.

Continental Mabor and Continental AG

Continental Mabor is the only manufacturing plant of tires in Portugal and is part of the German leader Continental AG. With an annual production volume surpassing 16.3 million tires, Continental Mabor is known for being one of the most innovative and productive plants in the group. For being constantly looking for innovative ways to improve their processes, Continental Mabor decided to launch this project and invest in a joint collaboration with the research institutions. More than a partner, Continental Mabor assumed a participative role in all development phases in the project. The fact that I had the opportunity to experience the shop floor reality, create my perspective and ideas from within the company, and access whatever data was needed, had a tremendous impact on the achievements of this research.

1.5 Dissertation Synopsis

The research done along this project covered aspects related different knowledge fields. All need to be integrated in the design and validation of a novel inspection system. Nevertheless, before defining the architecture of the novel system, this research suggests that first, a deep understanding of the current process should be obtained (Comprehension phase in Figure 1.4). Mapping and characterizing the current inspection process, together with its main limitations and constrains will provide inputs to the design phase of the novel solution (Development and Validation phase in Figure 1.4).

With the new system architecture established, an industrial prototype will be presented and special attention will be given to image acquisition, CAI, and automatic detection. Design of experiment methods will be used to validate the proposed system and conclude about its reliability. Finally the results obtained in the industrial prototype will be used to define a continuous development plan.

This dissertation is organized in seven chapters, including the introduction and conclusion. The first chapter aims at clarifying the research problem, research questions and research approach. Chapter 2 will be dedicated to the description of the current inspection process. An extensive field study was performed to capture the essential components and methods used by the visual inspectors. In chapter 3, a discussion about possible systems' design and levels of automation will be presented following the framework of well-established methods available in the literature. Chapter 4, 5 and 6, all of them related to the development and validation, will focus on: image acquisition station, CAI and automatic detection of imperfections, respectively. Finally, in chapter 7, the main outcomes will be address together with a suggestion of a methodology for continuous system development.

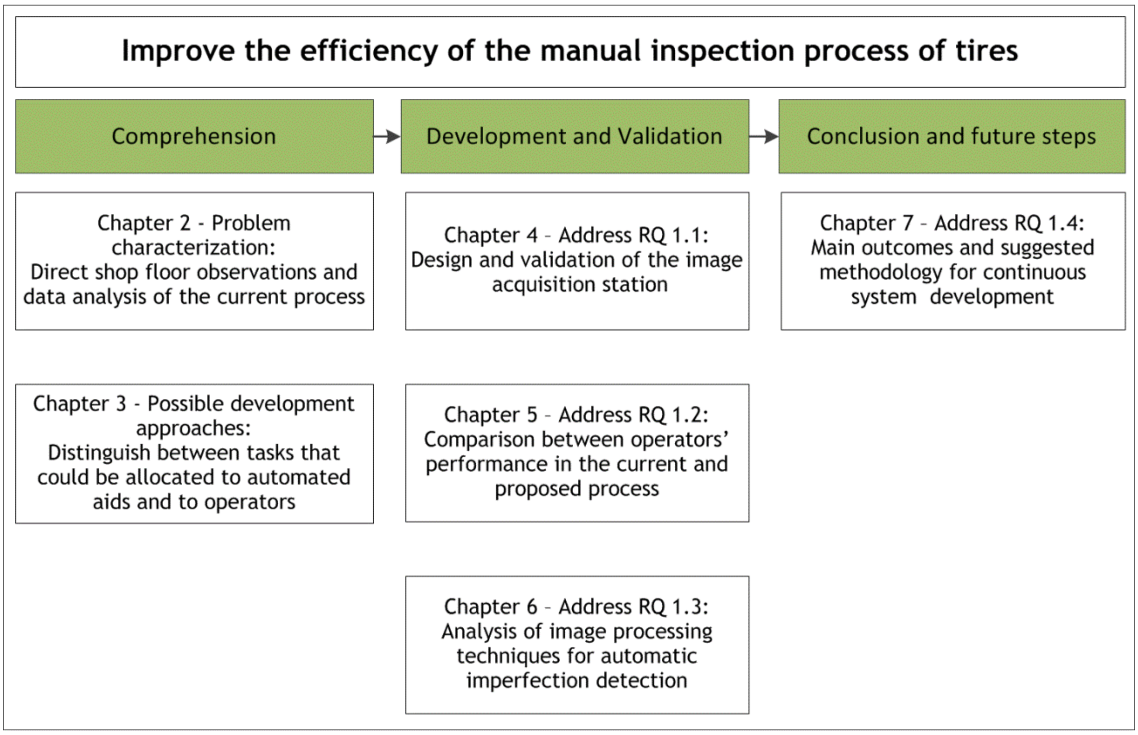


Figure 1.4 - Research topics and their correlation with research questions for a novel inspection system development.

1.6 References

Bargelis, Algirdas , Guenter Hoehne, and Aurimas Cesbulevicius. 2004. "Intelligent Functional Model for Costs Minimization in Hybrid Manufacturing Systems." INFORMATICA no. 15 (1):3-22.

Baudet, N. , J.L. Maire, and M. Pillet. 2013. "The visual inspection of product surfaces." Food Quality and Preference

Brosnan, Tadhg, and Da-Wen Sun. 2002. "Inspection and grading of agricultural and food products by computer vision systems—a review." Computers and Electronics in Agriculture no. 36 (2–3):193-213.

Busch, F. , C. Thomas, J. Deuse, and B. Kuhlenkoetter. 2012. "A hybrid human-robot assistance system for welding operations - methods to ensure process quality and forecast ergonomic conditions " Proceedings of the 4th CIRP Conference on Assembly Technologies and Systems

Consiglio, S., G. Seliger, and N. Weinert. 2007. "Development of Hybrid Assembly Workplaces." CIRP Annals - Manufacturing Technology no. 56 (1):37-40.

Cuevas, Haydee M. , Stephen M. Fiore, Barrett S. Caldwell, and Laura Strater. 2007. "Augmenting Team Cognition in Human-Automation Teams Performing in Complex Operational Environments." Aviation, Space, and Environmental Medicine no. 78 (5).

Dencker, Kerstin , Åsa Fasth, Johan Stahre, Lena Martensson, Thomas Lundholm, and Hakan Akillioglu. 2009. "Proactive assembly systems-realising the potential of human collaboration with automation." Annual Reviews in Control no. 33:230-237.

Drury, C. G. 2001. "Human Factors and Automation in Test and Inspection." In Handbook of Industrial Engineering - Technology and Operations Management, edited by Gavriel Salvendy. John Wiley & Sons.

ETRMA. 2011.

Fasth, Åsa , and Johan Stahre. 2008. "Does Level of Automation need to be changed in an assembly system? - A case study." Proceedings of the 2nd Swedish Production Symposium (SPS). Stockholm, Sweden.

Frosio, I., N. Alberto Borghese, P. Tirelli, G. Venturino, and G. Rotondo. 2011. Flexible and low cost laser scanner for automatic tyre inspection. Paper read at Instrumentation and Measurement Technology Conference (I2MTC), 2011 IEEE, 10-12 May 2011.

Gee, Linda A., Anne-Claire Legrand, Fabrice Meriaudeau, Christophe Dumont, and Mongi A. Abidi. 2000. Textures from stereo-based IR imaging for industrial tire inspection.

Gray, W. H. , C. Dumont, and M. A. Abidi. 1999. "Simulation Of A Tire Inspection System." Proceedings of the 5th Conf. on Quality Control by Artificial Vision.

Harrison, M. D. , P. D. Johnson, and P.C. Wright. 2003. "Relating the automation of functions in multi-agent control systems to a system engineering representation." In Handbook of Cognitive Task Design, edited by Lawrence Erlbaum Associates, 503-524.

Hoc, Jean-Michel 2000. "From human-machine interaction to human-machine cooperation." ERGONOMICS no. 43 (7):833-843.

Kaber, D. B. 2004. "The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task." Theoretical issues in ergonomics no. 5 (2):113.

Kaber, David B. , Emrah Onal, and Mica R. Endsley. 2000. "Design of Automation for Telerobots and the Effect on Performance, Operator Situation Awareness, and Subjective Workload." Human Factors and Ergonomics in Manufacturing no. 10 (4):409-430.

Killing, J. 2006. "A Neuro-fuzzy Approach to Machine Vision Based Parts Inspection." North American Fuzzy Information Processing Society Annual Conference.

Kim, Koung Suk , In Young Yang, Ki Soo Kang, Sung Mo Yang, and Seong Kyun Cheong. 2004. "Quantitative Evaluation of Defect inside Tire by Shearography." Key Engineering Materials no. 270:696-702.

Krüger, J., T. K. Lien, and A. Verl. 2009. "Cooperation of human and machines in assembly lines." CIRP Annals - Manufacturing Technology no. 58 (2):628-646.

Laofor, Chollada, and Vachara Peansupap. 2012. "Defect detection and quantification system to support subjective visual quality inspection via a digital image processing: A tiling work case study."

Lee, Su-Lin , Mirna Lerotic, Valentina Vitiello, Stamatia Giannarou, Ka-Wai Kwok, Marco Visentini-Scarzanella, and Guang-Zhong Yang. 2010. "From medical images to minimally invasive intervention: computer assistance for robotic surgery." Computerized Medical Imaging and Graphics no. 34:33–45.

Leveson, Nancy G. , and Everett Palmer. 1997. "Designing Automation to Reduce Operator Errors ".

Malamasa, Elias N. , Euripides G.M. Petrakisa, Michalis Zervakisa, Laurent Petitb, and Jean-Didier Legatb. 2003. "A survey on industrial vision systems, applications and tools."

Miller, Christopher A., and Raja Parasuraman. 2007. "Designing for Flexible Interaction Between Humans and Automation: Delegation Interfaces for Supervisory Control." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 49 (1):57-75.

Mital, A. . 1997. "What role for humans in computer integrated manufacturing?" International Journal of Computer Integrated Manufacturing no. 10 (1-4).

Moganti, Madhav, Fikret Ercal, Cihan H. Dagli, and Shou Tsunekawa. 1996. "Automatic PCB Inspection Algorithms: A Survey." Computer Vision and Image Understanding no. 63 (2):287-313.

Mueller, Max. 2013. "Automatic benefit " Tire Technology International

Parasuraman, Raja, and Dietrich H. Manzey. 2010. "Complacency and Bias in Human Use of Automation: An Attentional Integration." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 52 (3):381-410.

Parasurman, Raja , and Victor Riley. 1997. "Humans and Automation: Use, Misuse, Disuse, Abuse." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 39:230-253.

Pastorius, W., and M. Snow. 2006. "Smart laser vision sensors simplify inspection." Instrumentation & Measurement Magazine, IEEE no. 9 (1):33-38.

Säfsten, K., M. Winroth, and J. Stahre. 2007. "The content and process of automation strategies." International Journal of Production Economics no. 110 (1–2):25-38.

Sannen, Davy , and Hendrik Van Brussel. 2009. "Active Grading Ensembles for Learning Visual Quality Control from Multiple Humans." Lecture Notes in Computer Science no. 5519:122-131.

Schraft, Rolf Dieter, Christian Meyer, Christopher Parlitz, and Evert Helms. 2005. "PowerMate – A Safe and Intuitive Robot Assistant for Handling and Assembly Tasks." Proceedings of the 2005 IEEE International Conference on Robotics and Automation.

Sheridan, T. . 1995. Human centered automation: oxymoron or common sense? . In IEEE International Conference on Systems Man and Cybernetics. Vancouver, BC.

Takata, Shozo, and Takeo Hirano. 2011. "Human and robot allocation method for hybrid assembly systems." CIRP Annals - Manufacturing Technology no. 60 (1):9-12.

Tan, K. C. , R. B. Handfield, and D. Krause. 1998. "Enhancing the firm’s performance through quality and supply base management: an empirical study."

Wordsworth, Saul 2008. "Defect-free production through sensor technology." Tire Technology International.

Wordsworth, Saul 2011. "Mar or Machine?" Tire Technology International.

Chapter 2
Methods for manual inspection processes

The definition of strategies aiming at enhancing the tire inspection process performance and, implicitly enhance human inspectors' performance, requires further clarification of the current inspection process and the circumstances in which some its sub-components can fail. This would help in a later definition of possible improvement strategies.

The objective of this chapter is to first describe the mechanisms proposed in the literature associated to human inspection processes. Afterwards, a detailed description of the inspection process of tires is given.

2.1 The nature of manual visual inspection

Inspecting a product or system can be subdivided in three main tasks that the operator needs to fulfill: visual search, recognition and decision (Holmgren 1968). The study by Drury (2001) goes into further detail and divides inspection in five logical functions: set-up, present, search, decision, and respond. Both subdivisions suggest a linear sequence of functions but the authors also point out that in practice there can be some branches and reentries in the sequence.

Considering the five logical steps:

Set-up refers to the functionality check of the equipment needed by the operator. The equipment can be measurement devices, machinery, automation aids, decision aids, and recording mechanisms, among others. Verifying whether or not the equipment is operating properly is typically done by the human operator before initiating the inspection process.

Present is associated to the availability of the part or system to be inspected. The selected product or test must be presented to, and interfaced with the inspector (Drury 2001; Drury, Ghylin and Holness 2006).

Search is an active process in any inspection context, in which the operator looks for a *target* item among a set of *distractor* items. According to the application domain, this can include or not a phase of a rapid and global assessment, during which general spatial layout is determined, familiar structures or features are identified, and evident potential targets are noticed. This is typically called preattentive or distributed attentional (McCarley et al. 2004). The subsequent search requires detailed vision fixations. When the human operator fixates a point, visual acuity is highest along the line of sight and decreases into the periphery, falling off more rapidly in the far periphery. The useful field of view (also known as visual lobe) defines the limit of peripheral sensitivity for a particular target, commonly defined as the area visible in a single fixation (Chan and Chiu 2010; Melloy et al. 2006). The process of visual search is then described as a sequence of eye fixations in which the visual lobe is actively moved across the field of view (during which visual quality flaws may be detected). Generally speaking, information is absorbed during a fixation while peripheral vision plays a role in guiding and triggering subsequent eye movements (Scott 1993). Many authors studied the importance of co-operation between central vision and peripheral vision in the total performance of human vision (Chan and Courtney 1996). An example of this is an operator in supervisory tasks in a control room. The human operator needs to observe continuously and accurately several displays at the center of his visual field. Simultaneously the operator has to detect and make response to unpredictable signals that can occur in the periphery of the visual field. In some circumstances it becomes very time consuming and impractical to move the central vision to scan the entire field in a search task and so peripheral vision must be used in detection of a target in a search field (Chan and Chiu 2010).

The visual lobe area is affected by many factors such as the adaptation level of the eye, target size, background characteristics, individual differences in peripheral vision and individual experience (Gramopadhye and Madhani 2001). In fact, many studies suggest that experienced operators do not need as many fixations because they are able to extract more information from peripheral vision in a fixation than novices. In medical image reading, this effect was also reported since experienced radiologists were more likely than interns to fixate abnormal regions in a mammogram. Such increased effectiveness of visual scanning could reflect strategic expertise in planning scan paths or perceptual expertise in noticing and guiding the eyes toward peripherally viewed targets (McCarley et al. 2004).

Most industrial inspections are done to large visual fields and thus the human operators use eye movements between multiple fixations. In the literature the visual search performance appears to be highly influenced by the operator search behavior that can be either systematic or random. When random, the operator does not have memory of previous visual lobe locations while in systematic mode there is perfect memory and thus 0% overlap and unsearched regions. In practice, actual search behavior appears between these extremes (Melloy et al. 2006). Wang, Lin and Drury (1997) demonstrated that any memory of previous fixation locations improves search performance and suggested methods to train human inspectors to be more systematic. Baveja et al. (1996) studied the influence of partial overlapping between fixations in human search performance, concluding about suitable degree of overlap and its impact in the overall outcomes.

Decision in visual search refers to the output from the search function and can either be zero or non-zero (one or many) targets found (Drury 2001). In this step the operators perform what Rasmussen (1986) described as topographic diagnostic search, in which the operator compares the whole of what is currently being observed to a recollection or impression of a normal version (Woodcock 2014).

In a visual search task, decision rules should be objectively defined and described prior to the assignment of the task to the inspector. The definition of the decision rules is typically based on operational requirements such as quality standards in inspection or completion criteria for a maintenance job. The rules can be passed on by senior inspectors, or by means of complex and written decision procedures.

Typically, the rules are of one of three types:

Rule 1: IF the magnitude M_i of an indication of type (i) exceeds a severity S_i, THEN item is not fit.

Rule 2: IF the magnitude M_i of an indication of type (i) under circumstances (j) exceeds a severity $S_{i,j}$, THEN item is not fit.

Rule 3: IF the number of indications of type (i) with magnitude M_i exceeding severity S_i exceeds N_i, THEN item is not fit (Drury 2001).

There are circumstances in which a comprehensive definition and specification of all possible hazards is not possible or was not correctly formulated by the organization. In this situation, the quality inspection relies in the broad responsibility and experience of the human operators and their ability to recognize indicators of possible adverse outcomes (Woodcock 2014).

Respond involves actions taken according to a decision. Defective items being removed from a production system or a process being stopped are examples of possible responses. The inspector may also need to capture data and organize it in a form usable by the manufacturing system for subsequent corrective actions.

Understanding the sequence and interrelation of these five logical functions becomes clearer in the light of the cognitive model of human performance proposed by Rasmussen (1983). Other models of human performance, besides the one proposed by Rasmussen (1983), could have been use to characterize and frame the cognitive process of inspection. For not being the main research focus of this dissertation only Rasmussen's model is described in this document. This was selected for being the one more widely accepted in the literature for the description of inspection processes.

Known as skill-, rule-, and knowledge model (SRK), it considers that humans are not simply deterministic input-output devices but goal-oriented creatures that actively seek relevant information to take correct decisions. When confronted with a decision, humans recollect experiences from previous attempts, orient towards rules that were previously successful and develop mental representations for later use. According to Rasmussen (1983) and Rasmussen (1985), the knowledge representation for a decision maker can be structured in a hierarchically organized control system with three levels: skill-based; rule-based; and knowledge-based (Figure 2.1). At the lowest level (skill-based behavior) human performance is governed by patterns of preprogrammed behaviors and routine situations. Actions take place without conscious control. Typically, in skilled sensory tasks, the body of the human moves in synchronization with some sort of behavior of the environment. At the middle level, human performance is governed by conditional rules. These rules may have been derived empirically during previous occasions or communicated from other persons' know-how. Rule-based behavior is slower and more cognitively demanding than skill-based behavior since it is generally based on explicit know-how. However, the boundary between skill-based and rule-based performance is not quite distinct, and much depends on the level of training and on the attention of the person.

During unfamiliar situations, faced with an environment for which no know-how or rules for control are available from previous encounters, the control of performance must move to a higher conceptual level, in which performance is goal-controlled and knowledge-based. In this case, alternatives are considered and tested either physically, by trial and error, or conceptually.

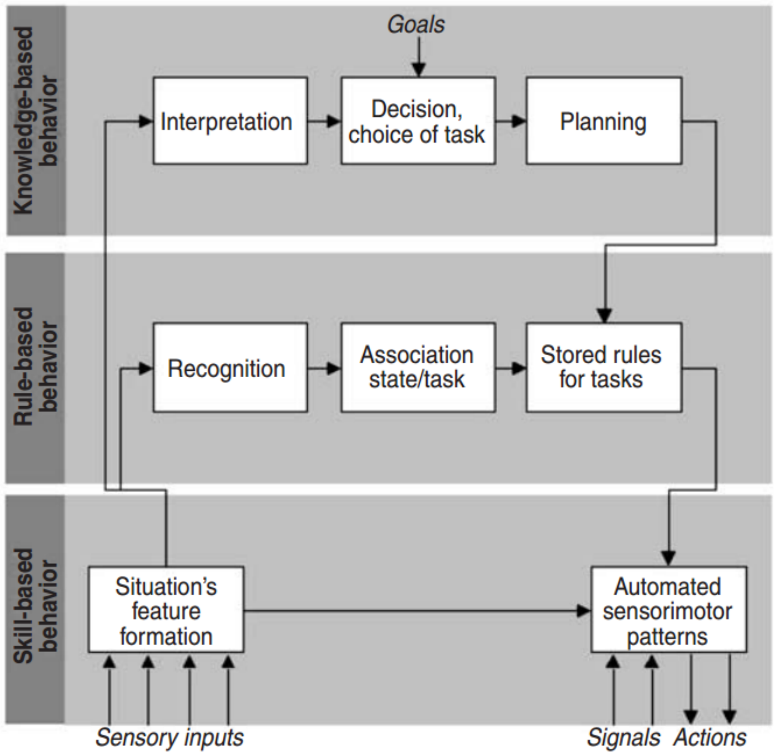


Figure 2.1 - The Skill, Rule, and Knowledge-Based Model (Rasmussen 1983; Marmaras and Kontogiannis 2001).

In inspection, the first two logical functions (Set-up and Present) and the last (Respond) typically do not recall higher-level behaviors. Entering the rule-based level is only necessary in cases in which, for example, changes in the setup to accommodate different customers, different products, or different process conditions are needed (Drury 2001).

Also search is mostly a skill-based activity (Baveja et al. 1996). With training, practice and experience, human inspectors tend to perform search almost automatically with minor cognitive effort (Chiu and Chan 2007). Individual differences can significant affect the search activity. Besides visual acuity, the visual lobe area and shape have been found to be important and to be related to visual search performance (Chan and Chiu 2010; Chiu and Chan 2007). For this reason, there are some studies suggesting some standard measurements to help in selecting inspectors with better visual capabilities and, therefore, possibly better search performance potential. Instead of a random selection of inspectors which could result in training persons with poor capability and possibly poor potential, the selection tests may help in improving overall inspectors' performance (Chan and Chiu 2010).

Authors also reported that, within search, there is some rule and knowledge-based components, especially when it comes to defining a search plan and path and in determining a stopping policy. These higher-level behaviors allow, for example, an experienced medical image reader to immediately check regions most likely to contain an abnormal feature (McCarley et al. 2004). In fact, an important aspect of the human behavior is the ability of performing a guided search based on prior information. If this knowledge exists, locations more likely to contain items of interest are searched in first place (Wolfe 1994). Choice of how long to search before deciding that no target exists is another aspect of the search process that requires knowledge or rule based components. Although the probability of detection increases with time spent searching, there are often throughput targets that the inspector needs to fulfil (Drury 2001). The difficulty is that speed and accuracy are known to co-vary negatively for some tasks. Thus, models to define and optimize a stopping policy have been suggested (Hong 2005). Aspect such as costs, payoffs and probabilities should be considered.

In practical situations, visual search takes longer than the decision-making process. Typically, decisions are rule-based which may suggest that rule-based behavior controls this logical step. Yet, the three hierarchical levels can contribute likewise in the search step. At the lowest level (skill-based) are extreme situations in which there is a total absence or an obvious indication of flaw. In these cases the decision will be trivial and essentially skill based. Most decisions, however, are nontrivial and require higher-level behaviors. In the most cognitive demanding situation, the operator has to decide consciously and based on the potential consequence of an incorrect decision. Usually, false positive and miss errors do not have equal weights, because falsely accepted components may result in system failure. Thus ambiguous detection situations can become highly complex and subject to errors (Drury 2001).

The scientific interest is mostly related with the visual search and decision steps. The compelling observation that while some targets are found immediately, others require careful and serial strategies to be found, motivated many studies and the development of various models (Nothdurft 2006). Effortless detection can take place almost instantaneously in preattentive search by the "pop-out" effect, a term frequently used in visual search literature. The idea that, in some circumstances, the odd element will effortlessly "pop out" from the background and call attention to its location is generally accepted (Luck and Hillyard 1994). The "pop-out" effect is sensible to basic features like orientation, color and size (Figure 2.2). "Pop-out" in the context of visual search can also be defined as conspicuous "pop-out" or salience (Nothdurft 2006). Relating the effect of "pop-out" with the reaction time and with background characteristics is also of interest. If the target is the only salient item in a pattern, it should be found immediately, almost independent of the number of other items available. An example of this is to find a red item among green (Wolfe 2003). If, on the other hand, there is no salient item, the target cannot be easily selected, and several other aspects must be checked (Figure 2.3). In this case, search time will increase as the number of distractors or size of the field of view increases (Nothdurft 2006). An example described in the literature is to search for a randomly oriented "T" among "L"s. In this case the search would need to proceed in a serial manner, from item to item until the target was found or the search was abandoned (Wolfe 2003).

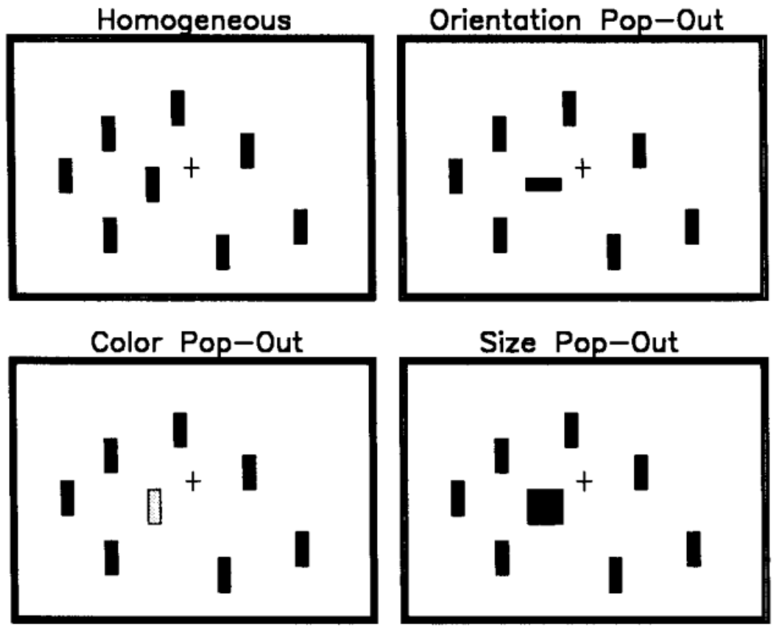


Figure 2.2 - Examples of the homogeneous, orientation pop-out, color pop-out and size pop-out stimulus array (Luck and Hillyard 1994).

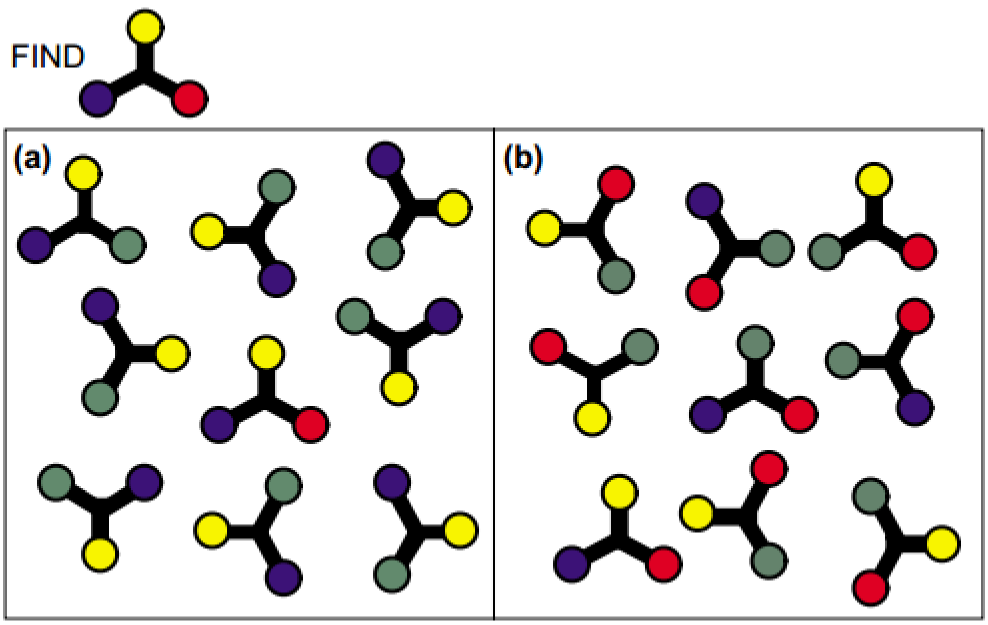


Figure 2.3 - Example to illustrate why some search tasks are easier than others. Finding the target blue-yellow-red 'molecule' is trivial in (a) because of the unique red element. Search is much less efficient in (b) because no unique feature defines the target (Wolfe 2003).

2.2 Human errors

Inspectors play a significant role in any safety or quality inspection system. Multiple social and organizational factors can affect operator's performance, and it is unreasonable to expect consistent performance across all conditions and time periods (Ballou and Pazer 1982).

Ergonomists and human factors engineers have attempted to justify human errors with poorly designed man-machine interfaces. Thus the increase in the system reliability was thought to be mostly related with strategies to redesign this interface. This is understandable and desirable, but it tends to obscure a crucial aspect: "that even with the best-designed man-machine interface, the probability of human error cannot in practice be reduced to zero except, of course, by decreasing the output rate to zero also" (Sylla and Drury 1995).

The performance of an inspection process is measured by the accuracy achieved which is the probability of discovering a target in a certain time range. In practice, measuring the performance of an inspection system aims to find out how well the decisions made by one operator match the decisions that should have been made. Typically each decision is a binary one and the outcome can either be: conforming (OK)/nonconforming (NOK) or good/faulty. Thus, inspection performance can be defined by a set of probabilities according to the agreement between decisions and true state of conforming:

- p_1 probability of deciding that a conforming item or process is conforming
- p_2 probability of deciding that a nonconforming item or process is nonconforming
- $(1-p_1)$ probability of deciding that a conforming item or process is nonconforming
- $(1-p_2)$ probability of deciding that a nonconforming item or process is conforming

Signal detection theory can be used to classify inspection performance. Decisions can be classified as hits (correct rejection of defects), misses (acceptance of defect), false positives (rejection of acceptable condition) and correct acceptance of non-defective products by comparing actual decisions to correct decisions (Woodcock 2009). The possible outcomes are summarized in Table 2.1.

Table 2.1 - Possible outcomes of inspection (adapted from Drury (2001)).

Decision taken	*Item conforming*	*Item nonconforming*
Accept	Correct Accept	Miss
Reject	False positive	Hit

Considering the framework proposed by Drury (2001), search and decision are traditionally the two areas with the highest occurrence of errors as they mostly rely on the inspectors' individual abilities (Ghylin, Drury and Schwaninger 2006). Even though, errors can occur in every step and the circumstances associated to each are dependent on the environment under analysis. A typical search error is missing a target and a typical decision error is misclassifying a target (Ghylin, Drury and Schwaninger 2006). Table 2.2 defines the possible generic errors that can occur in the two main functions of inspection (Search and

Decision). For each level of the SRK model, there are different error causations. While in the skill-based, mistakes occur in some routine tasks associated with some form of distraction or preoccupation, in the rule and knowledge-based levels, mistakes are due to misapplication of the adequate rule or application of a wrong rule. Although humans are "furious pattern matchers", in some circumstances the application of rules of thumb or heuristics may go wrong (Reason 2005).

Table 2.2 - Analysis of generic errors associated to Search and Decision in the scope of SRK model.

	Possible errors	
	Search	Decision
Skill-based behavior	1. Failure to detect/locate a target 2. Detect a nontarget	For immediate decisions: 1. Deciding that a conforming item is nonconforming 2. Deciding that a nonconforming item is conforming 3. Failing to invoke the decision process
Rule and knowledge-based behavior	1. Choose a search path that leads to areas being entirely neglected 2. Search terminated too quickly	For complex decision: 1. Incorrect decision due to the invocation of the wrong rule 2. Incorrect decision due to the misapplication of the correct rule

The basic premise when analyzing a process dependent of human decisions is that humans are fallible and errors are to be expected, even in the best organizations. Because the human errors are not constant and can occur in the various steps of the process as described in Table 2.2, tracking procedures and definition of root cause can become extremely difficult. Two approaches to the problem of human fallibility exist (Reason 2000). Dekker (2006) suggested the dichotomy "Bad Apple" and "New View" to distinguish between them. In "Bad Apple" theory, the assumption is that people can simply choose between making errors or not and whenever errors occur the most probable causes are aberrant mental processes such as forgetfulness, inattention, poor motivation, carelessness, negligence, and recklessness (Reason 2000). Investigations following Bad Apple theory often end up concluding "They did not try hard enough. They should have looked a bit better, or concentrate a bit more". The "Bad Apple" theory remains the dominant tradition in medicine and aviation (Reason 2000). On the other hand, the "New View" assumes that people do reasonable things given the complexity, dilemmas, trade-offs and uncertainty that surrounding them. In an industrial process, for example, besides keeping quality standards, the operators have to usually cope with multiple other objectives such as pressures to produce, to not cost unnecessary money to the organization, to be on time, to get results, etc. People's different sensitivity to these objectives and the process of juggling them in parallel can create some vulnerabilities in the decision process. The ambiguous evidences and uncertain outcomes may lead to the occurrence of mishaps or errors. Following the “New View” the idea is to avoid judging and blaming but rather asking the reason why a certain decision made sense in that context. Errors in this sense are a symptom of trouble deeper inside a system that deserves further investigation (Dekker 2006).

In inspection processes, the occurrence of errors has been reported to be affected by many factors such as time allowed for inspection, work environment, inspector’s fatigue, and other work and inspection related aspects (Duffuaa and Khan 2005). This lead to the distinction between two sets of factors: active and latent failures. Active failures are unsafe acts (errors) committed by those at the “sharp end” of the system (e.g. inspectors, anesthetics, surgeons, pilots, crew members). They are the people whose actions have immediate consequences. Latent failures are created as the result of decisions taken at the organizational and management spheres (Reason 2000; Reason 2005). Fully understanding human errors and the organizational and human factors that surround them, benefit from a system approach instead of isolating errors from their context. The direction of causality is illustrated Figure 2.4. From left to right, bad decisions begin with negative consequences of organizational processes (i.e. decisions concerning planning, scheduling, designing, specifying, etc). The latent failures are transmitted along various organizational and departmental pathways to the workplace and worker (e.g. undermanning, fatigue, inexperience, etc) that ultimately potentiate errors. Many incorrect actions can be committed but only few of them transpose the defenses created by the operators to avert errors or mitigate their effects (Reason 2005).

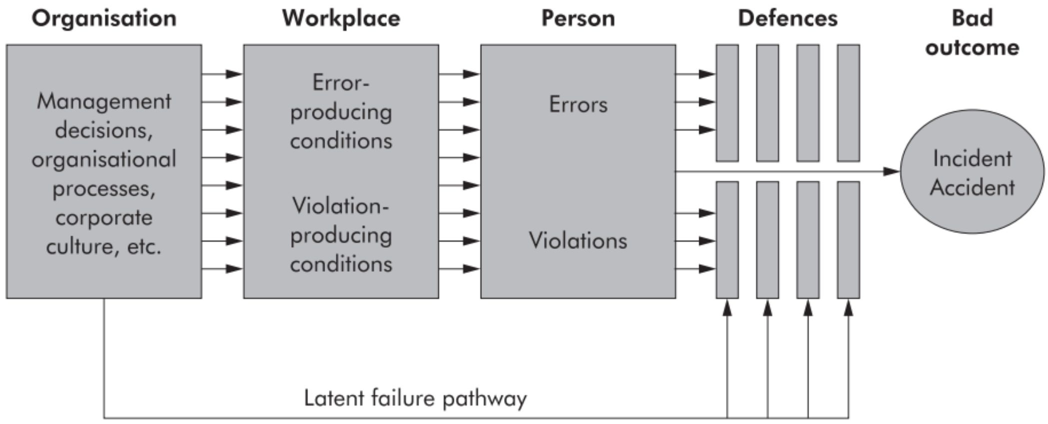


Figure 2.4 - Stages in the development of an organisational error (Reason 2005).

These concepts of human performance and human error will be used in the following sections of this document, first in the analysis of the current inspection process of tires and later as considerations for the system re-design process. In the current inspection of tires, deviations of the standard procedures occur and so do human errors. Following the “New View” approach, we propose that a good understanding of these aspects, including human and organizational dimensions, can contribute to a more adequate re-design of the process. Instead of following the approach of reducing the unwanted variability in human behavior by moving them away from the process, the objective is to re-design the inspection system accounting for aspects such as workers, team, inspection task to be done, workplace, and the organization as a whole.

2.3 Manual inspection in the tire industry context

The following two sub-sections provide brief background information regarding the structure of a tire and its manufacturing process. This knowledge will then be useful for a better understanding of the inspection process and its manufacturing context. Subsequently, the inspection process will be described in detail, followed by a discussion of process deviations and human variability.

2.3.1 Tire fundamentals

The primary function of tires is to provide the interface between the vehicle and the road. The contact area with the road is made by the tread, while the sidewalls are the lateral areas that, with the corresponding inner liner, form the compartment for the compressed air. The tire carcass also includes the bead and shoulder. The bead is in direct contact with the rim on the wheel and because it is typically reinforced with steel, increases the sidewall stiffness. The shoulder is the transition area between the tread and the sidewall (Figure 2.5).

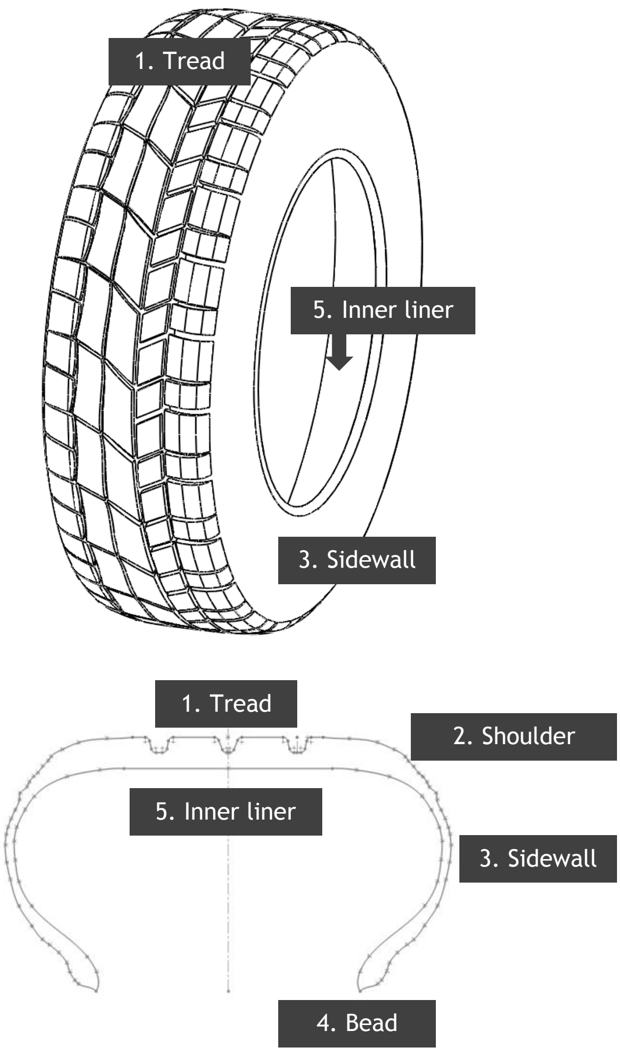


Figure 2.5 - Illustration of the tire carcass composed by several parts: tread (1), shoulder (2), sidewall (3), bead (4), and inner liner (5).

Tires are highly engineered structural composites whose specifications should be selected according to the requirements of the vehicle and customer driving conditions. Aspects such as load carrying requirements, typical weather conditions and road surface irregularities should be considered when selecting a tire (Lindemuth 2006). To meet the various requirements, the dimensions and the components of the tires can be adjusted. A combination of 60 different raw materials including rubbers, fabrics, steel wire and cords, is needed to produce a tire.

The pneumatic tire manufacturing industry follows many safety requirements and government regulations, stressing the importance of the quality of tires. The complexity of the legislation is increasing and the main focuses are in testing procedures to check compliance and safety and environmental concerns. The industry is continuously adapting products and production processes and making technological adjustments to attempt to meet international and EU level regulations. Limits on rolling noise, rolling resistance (that influences fuel consumption), wet grip on the product-level and waste restrictions, chemical usage declarations and reduction of CO_2 emissions on the manufacturing facilities are just some examples (ETRMA 2010).

The legislation also requires tire manufacturers to place standardized information on the sidewall of all tires. This information identifies and describes the fundamental characteristics of the tire and also provides codes for tire identification such as DOT (Department of Transportation) (NHTSA 2001) (Figure 2.6).

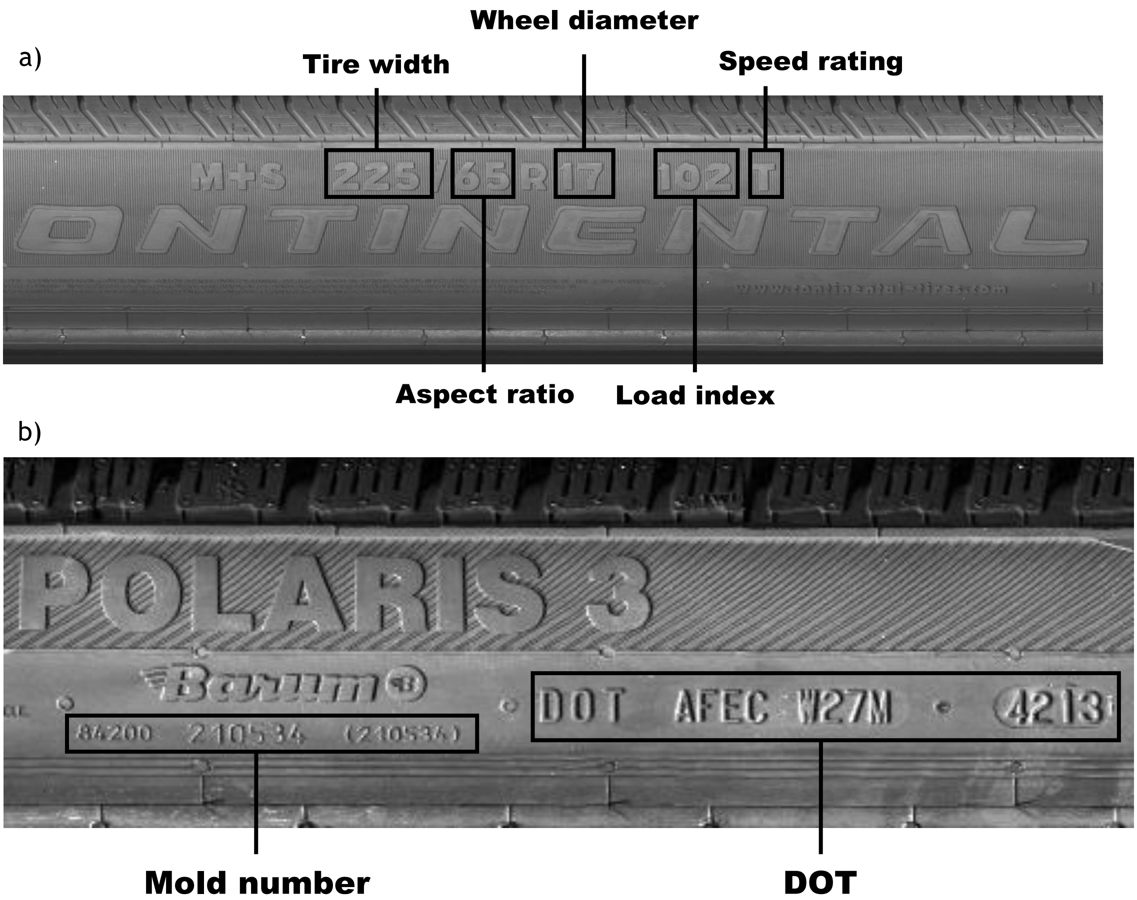


Figure 2.6 - Description of tire codes embossed on tire sidewall (a) Dimensional information, (b) Mold number and DOT.

In Figure 2.6 a) the first set of 3 digits represents the width of the tire, measured from sidewall to sidewall, in millimeters. The second indication, known as the aspect ratio, gives the tire's ratio of height to width which results in the height of the sidewall (as an example, in the case of the tire in Figure 2.6, the height of the sidewall is 60% of 205 mm). After the rim diameter in inches, the tire's load index is embedded. It is a measure of how much weight each tire can support. The set of dimensional information finishes with the maximum speed rating which denotes the maximum speed at which a tire is designed to be driven for extended periods of time.

Besides dimensional information, the sidewall also includes the mold number and DOT. Mold number is useful for tracking back to the original mold where the tire was manufactured. DOT is mandatory by the U. S. Department of Transportation and is an alphanumeric set of characters that contains the manufacturing plant code, date of production and other numbers that are marketing codes useful to process contacts with customers (Figure 2.6).

2.3.2 Tire manufacturing process

As mentioned before, many different raw materials are needed to manufacture a tire. Many industries are involved and, in order to guarantee quality within the manufacturing process, the tire manufacturer needs to seek suppliers that provide detailed certification of the properties and composition of the raw materials (Figure 2.7). After mixing, the rubber components are shaped by extrusion to form treads, sidewalls and beads (preparation hot). By a process of calendaring, the cords of textile and steel are aligned in pre-defined manners (preparation cold). Building refers to the process of components assembly which takes place in a machine operated manually that held together the components mechanically. The output of the building machine is a "green tire" which is a fully assemble uncured tire. An uncured tire presents a low Young Modulus, does not maintain its shape when deformed and can be very sticky. After being built, the "green" tire is stored on a rack that will then be transferred to vulcanization (curing).

Vulcanization is the actual process of linking rubber molecules. The network of rubber molecules increases elasticity while decreasing plasticity. Thus, vulcanization reduces the amount of permanent deformation after removal of the deforming force (Coran 2013). In vulcanization the "green" tire is placed in the mold over an inflatable bladder. The bladder forces the tire against the mold, forming the sidewall and tread patterns and letterings. After vulcanization, the tires are sent to the final finishing area by means of a conveyor system. Although the general principle of this step is simply to filter and forward only defective-free tires to the subsequent step, there are multiple criteria and methods to do so (Figure 2.7).

For an OK tire the Final Finishing process includes: visual inspection and uniformity tests (Figure 2.8). Visual inspection, as previously referred in this document, is a manual-based process. Inspectors' main functions are to trim off vents, to identify the tire, to observe its surfaces and identify potential visual imperfections. If no visual imperfections are found, the operator places the tire in a conveyor to be transported to the Uniformity machines where structural parameters are measured by means of laser sensors. Parameters such as radial force variation, harmonic waveform and conicity are measured.

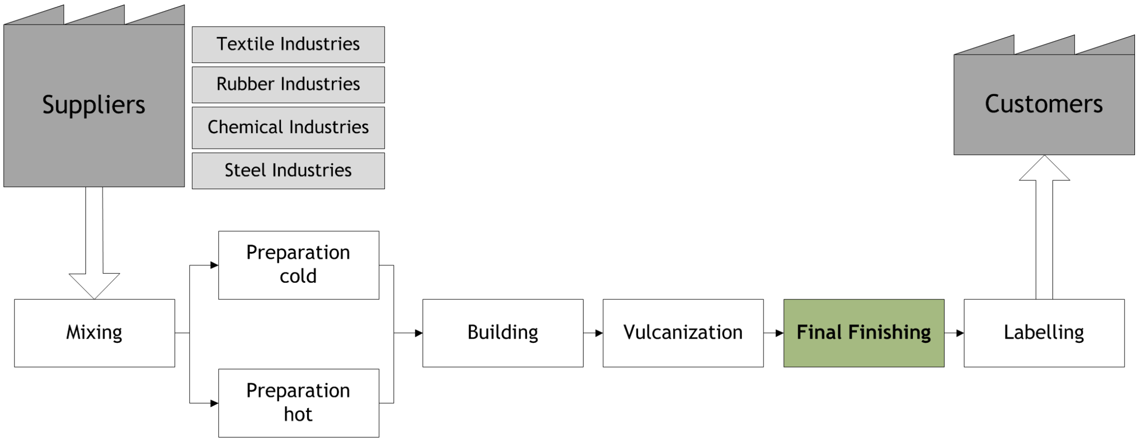


Figure 2.7 - Generic tire manufacturing process.

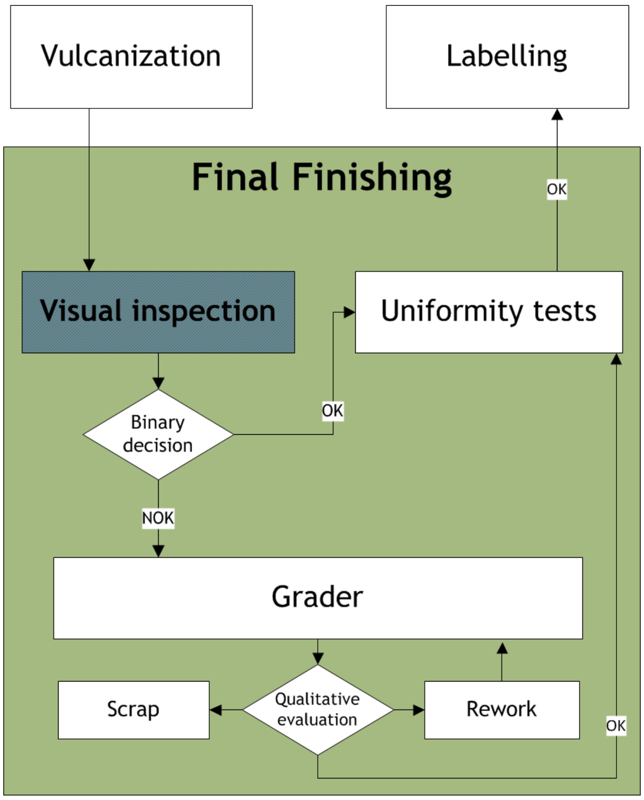


Figure 2.8 - Diagram illustrating the process flow in the Final Finishing area.

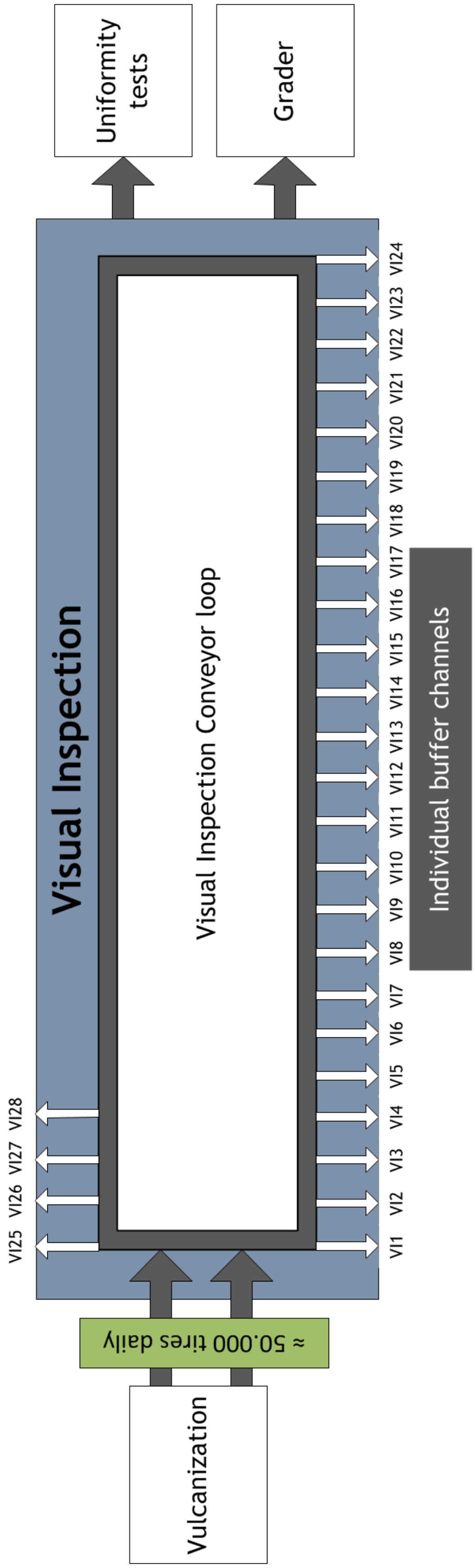


Figure 2.9 - Diagram with the layout of the Visual Inspection process within the industrial partner.

In case the inspector identifies an imperfection in a tire, the subsequent step is to forward it to the Grading area. Graders are operators belonging to the Quality Department that make a deeper analysis of rejected tires. Their level of expertise and experience, suits them for a decision process no longer binary but involving the determination and classification of the severity of the imperfection. Depending on the extent of the imperfection, the grader decision can be scrap, rework or false positive and thus immediately upgraded to OK. A tire that is sent to rework can then be fully recovered and re-classified as OK by the Graders. If that is the case, the tire continues the process as a regular OK tire converging towards the Uniformity area (Figure 2.8).

In the Continental Mabor facilities, the layout of the Visual Inspection process follows the illustration in Figure 2.9. The diagram does not intent to reproduce the layout in rigor and with detail. Especially the conveyor system is dramatically more complicated that the one illustrated. The daily production volume (≈50 000 pieces) flows through two channels and converge to a circular loop. From this loop the tires are randomly distributed to the visual inspectors (VI). 28 stations are available although typically only 24 operators are working simultaneously. Each station is fed by an individual buffer that can contain a maximum of 6 tires. The operators are positioned side by side with each other in two lines of machines, a larger one containing 24 stations and second with 4 stations. In the larger line, the operators can only leave the workplace near the extremities either close to VI1 or VI24. A global picture of the real layout is shown in Figure 2.10.

Figure 2.10 – Overview of the visual Inspection process at Continental Mabor.

2.3.3 Visual Inspection procedure and criteria

Visual inspection is a manual process done by specialized operators. Before being certified as inspectors, the operators have to undergo a period of learning and supervised training. At first, the inspectors are taught the methods and standard procedures to perform inspection as well as the rejection criteria. When a minimum knowledge is established, the operator is then allocated to a station. The tires inspected by the novice are not automatically forward to the subsequent step but rather re-inspected by an experienced inspector.

The workplace is composed by a set of equipment (Figure 2.11). The individual buffer, mentioned before, is positioned above the eye-level of the operator. When a tire is requested by the operator, it slides due to the slope of the conveyor exit and enters the inspection machine. The inspection machine contains two motorized rotation axes that automatically start rolling when the tire reaches the machine. In addition to smaller components, the workplace also includes a computer with a touch screen display, a barcode reader, a mirror for indirect observation angles and two exit conveyors. The working position of the operator is standing, typically aligned with the center of the machine and facing the front view of the tire (sidewall). The machine height intends that the operator eye-level is above or at the same height of the highest point of the tire so that the operator is always looking downwards and not upwards.

Figure 2.11 – Example of a VI workplace at Continental Mabor.

As described in the first section of this chapter, the first step in the process is *set-up*. In the context of tire inspection, this corresponds to the verification of the equipment operational conditions and operator's login. When the first tire is *present*, the machine is activated and starts rotating automatically one entire tire turn. While the tire is rotating, the most significant component of *visual search* occurs. As the tire is a complex and intricate object with multiple curved surfaces, the visual search does not occur in a single plane but rather on a tridimensional space. When the tire is rotating, the operator is:

- Observing the sidewall and the bead that are facing his standing plane and so directly visible (Figure 2.12);
- Checking the tread by means of a mirror usually on his right side;
- Inspecting the inner liner visually and haptically. Operator visual fixation towards the opposite side of the inner liner on the lowest part of the tire occurs while his hand senses the inner liner on his side and thus visually hidden (Figure 2.12).

Although called visual inspection, the standard procedure includes other tasks besides inspection itself. Inspection gives name to the process for being the main purpose and with recognized importance in the organization. Figure 2.13 illustrates the standard inspection process.

In addition to the visual search operation, the inspector also trims excessive material from the tire if necessary. Trimming is needed if there are vents or flash on the outer surface of the tire. These are created in the curing process when uncured rubber erratically flows and cures inside vent holes or in between mold segments. Although crucial in the curing process to avoid that air gets trapped in the tread, vents have the downside of eventually getting obstructed. There can be thousands of vents in a mold which enlarges the probability of clogging. Flash is typically a continuous excess of rubber that can occur in the shoulder or sidewall while vents are small protuberances in the tread. Both are cut with a knife. If existing, flash is mainly present in a particular location in the tire, right in the transition between sidewall and shoulder. In the vulcanization cavity, this location corresponds to a transition between segments of the mold.


Figure 2.12 – Visual and Haptic Search in the tire quality inspection process. On the left a detail of a simultaneous downward sidewall observation and trimming is shown while on the right the operator is inspecting the inner liner both visually and haptically.

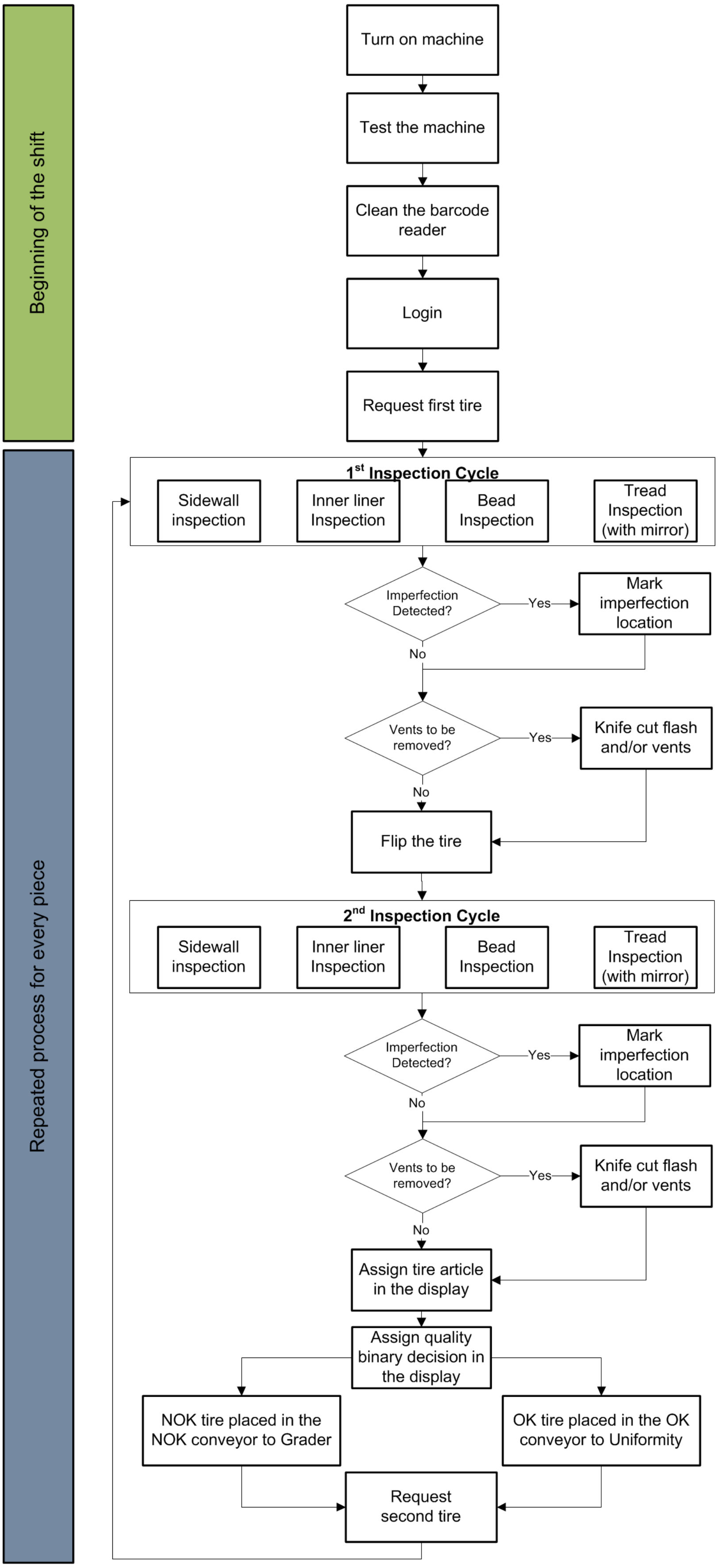


Figure 2.13 - Standard procedure to perform tire quality inspection at Continental Mabor.

The almost predictable location of flash allows operators to cut flash nearly automatically in a inattentive mode following a skill-based level behavior as described by Rasmussen (1983). For this reason, the operator can simultaneously cut flash and visually search the tire for imperfections. An example of the interconnection between these tasks can be seen in Figure 2.12 in which the operator is cutting flash while visually searching the sidewall and bead.

The machine automatically rotates the tire one complete turn. After that the rotation stops and the operator turns the tire around. Subsequently the machine performs the second rotational cycle enabling the inspection of the opposite side of the tire. At the end of each of the two automatic cycles (which dictate the minimum cycle time of inspection) the operator assumes the control of the machine and, if necessary, can re-activate the rolling of the cylinders to conclude inspection and/or trimming. The rotational speed of the cylinders is fixed in both automatic and manual control. On average the inspection time of one tire is 30 seconds. As described before, during the inspection cycle time, all surfaces of the tire need to be observed. Imperfections can occur in any tire surface and for this reason all need to be visually scanned by the operator. Besides the wide-range of possible locations, imperfections also vary significantly in shape, dimension, and visual appearance. The current off-standard catalogue approved by Continental contains a total of 76 different non-conformity (NC) codes. Imperfections include: stain, blemish (round or elongated), scratches of variable extension, blister and foreign material, among others (Figure 2.14). For the inspector to be accountable for the detection of a certain imperfection there must be a visual erratic manifestation. Imperfections that do not cause a visual artifact (unbalanced position of rubber, blisters in between interior layers, etc.) need to be identified by other means. This type of non-visual imperfections are classified in other categories and can be detected in uniformity tests, for example. Therefor they are out of the scope of the current visual inspection and will not be accounted for by the system proposed in this dissertation.

Although 76 NC codes exist, there is significant concentration of cases in specific codes. The analysis of historical data of a six-month period reveals that the ten most frequent codes represent 79% of total occurrences (Figure 2.15). Being more frequent in this case does not mean being more critical and for this reason, explicit instructions are given to the operators highlighting the equal importance of all imperfections' codes.

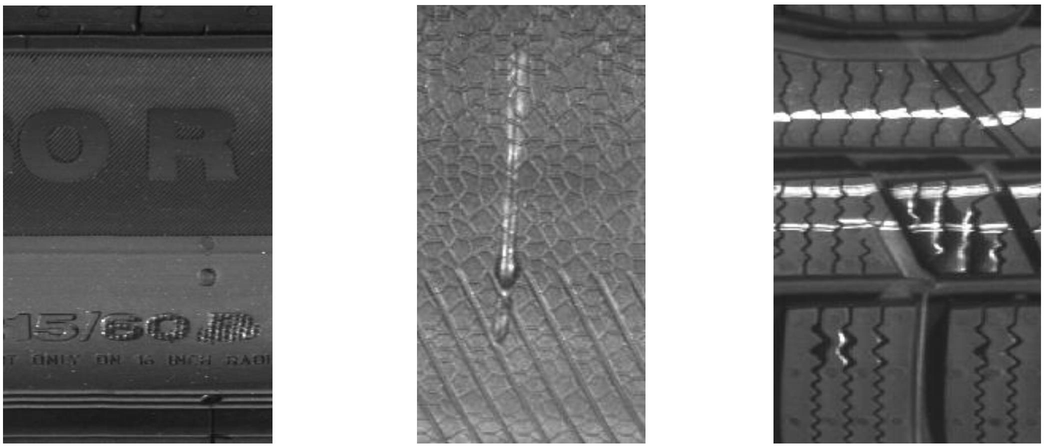


Figure 2.14 – Examples of imperfections in tires. From left to right a blemish in the sidewall, a blister in the inner liner and a blemish in the tread are shown.

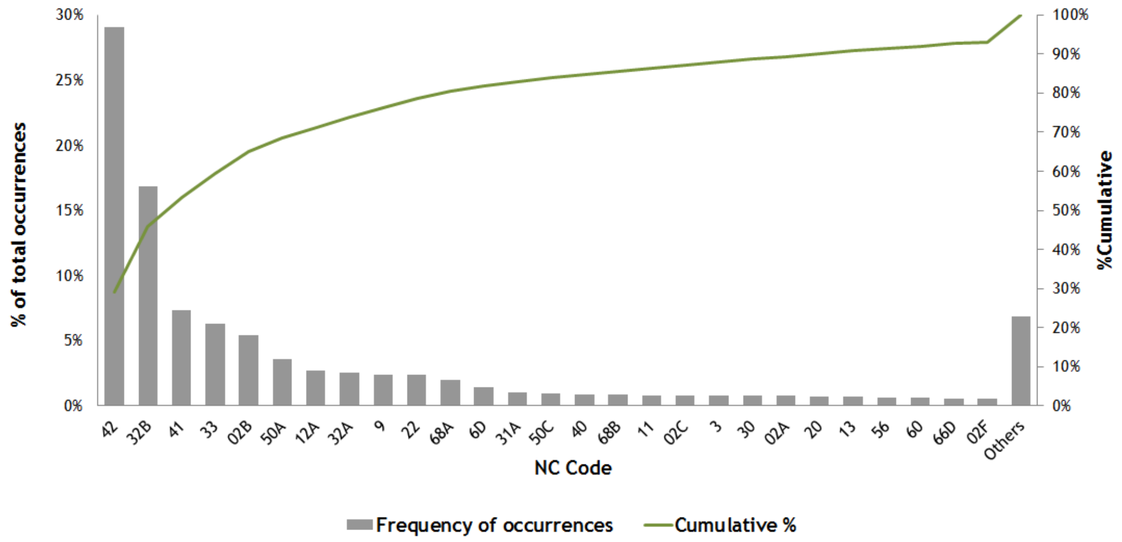


Figure 2.15 - Distribution of imperfection codes for a period of six months.

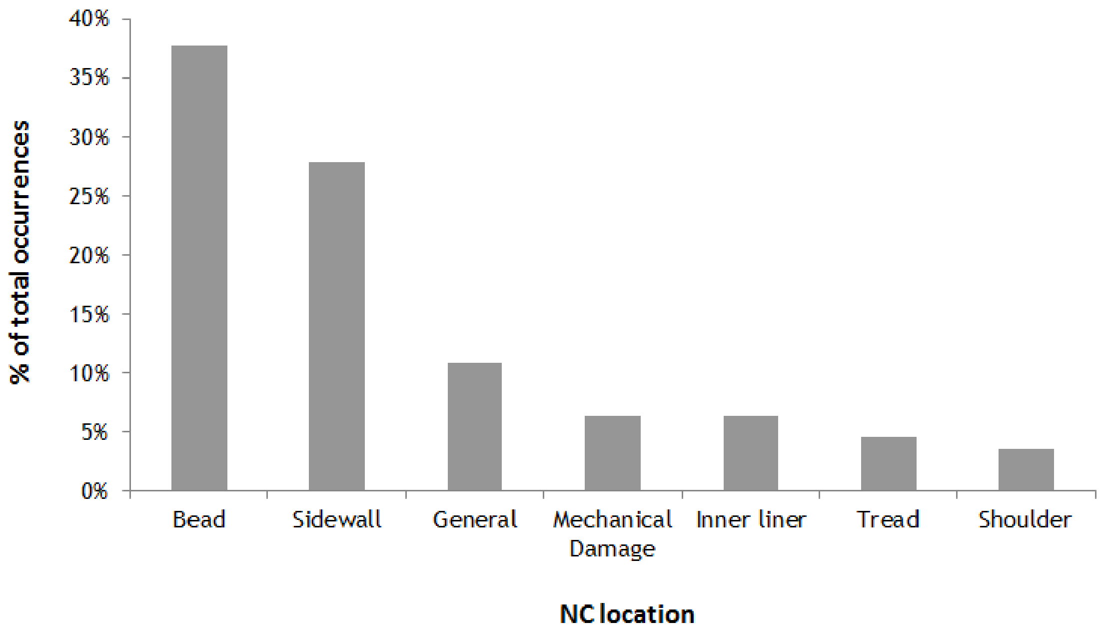


Figure 2.16 - Histogram of the distribution of NC occurrence across tire areas.

In addition to a high concentration in the occurrence of certain NC codes (Figure 2.15), the analysis of historical data also demonstrated that there are tire areas more affected than others. Figure 2.16 shows that the bead and sidewall are the two areas where most NCs occur. The categories “General” and “Mechanical areas” refer to imperfections that are not specific of a certain tire location. Foreign material is an example of a “General” NC since the unexpected excess of material can be anywhere in the tire. On the other hand, there are imperfections only evident in the inner liner or tread.

Besides an exhaustive description of defect types, the off-standard catalogue also discriminates the rejection criteria. The criteria are typically defined with one or more indicators such as number, maximum size, maximum depth and maximum height. Considering the example of a blister in the sidewall, the rejection criterion is as follows:

- A maximum of *x* blisters, each of them with a maximum diameter of *y* mm;
- A blister deeper that *z* mm;
- A blister higher that *w* <mm.

Blisters in the inner liner have other rejection criteria. The fact that the rejection criteria are defined in metric dimensions is sometimes difficult to be applied in the production line considering the fact that the operators do not have a tool to perform the measurements. For this reason the decision level of this inspection process is mostly based on the reasoning, training and experience of the operators. In any case the indications given by the organization to the operators suggest rejection of a tire in case of doubt.

In case an imperfection is visualized and interpreted as resulting in a non-confirming product, the operator marks the location of the imperfection in the tire with a coloured wax for a posterior analysis by the graders. When the visual search and trimming are finished, the operator concludes the inspection cycle by associating in the information system (through the interface in the display) the tyre article and the respective quality decision. A set of tires of the same “green” tire can be cured in a variety of different vulcanization molds and thus resulting in distinguished final products. The visual inspector is the first intervenient in process after vulcanization and for this reason, responsible for assigning the final article to the product.

Being *visual search* and *decision* phases concluded the remaining step is *respond*, which in this case corresponds to the action of releasing the tire to one of two conveyors according to the decision made. Handling the tire to the correct conveyor is a very physical intensive task and absenteeism due to back pain and or musculoskeletal disorders is common.

As one can see the inspection process as design today encloses the accomplishment of several tasks by the operator. Some tasks are directly linked to the inspection itself (visual search, quality decision, registration of the quality decision in the information system) while others seem to have been conveniently added to the process to reduce process steps and take advantage of human multitask capabilities to reduce costs (for example, trimming and tire identification). Identifying the percentage of time allocated to each of the sub-tasks is difficult to be estimated because as mentioned before there is some task parallelization and overlap. Even though, several time measurements were registered by observing operators performing inspection in the shop floor. These measurements were obtained by observations done by multiple researchers in different periods of the shifts. Figure 2.17 highlights the significant weight of the trimming which, in this particular testing sample exceeded the inspection time itself. This outcome cannot be generalized as the results may have been influenced by temporary or seasonal external factors such as: higher production of winter tires results in more tires that need trimming and high production volumes can also decrease the opportunities to perform maintenance in the vulcanization area and thus increasing the clogged vents. The 15% of time spent in other activities include: tire identification and tire handling. The purpose of these measurements was only to have a rough estimation of the relative importance of each component. Values presented in Figure 2.17 result from the average of several measurements and should not be assumed as fixed.

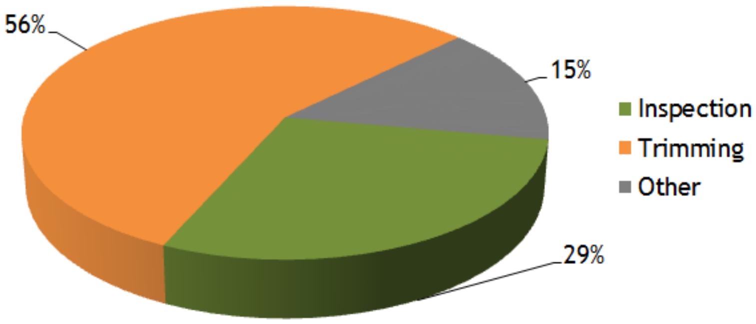


Figure 2.17 - Time allocation to the several tasks included in the inspection process.

2.4 Variability, heuristics and deviations in tire manual inspection

When analysing in detail the inspection process of tires, one evident aspect is the significant variability in performance among operators. Two aspects were compared across operators, being the first one the inspection time. As mentioned before the average inspection time of a tire is approximately 30 seconds. The information systems at the shop floor level enabled a more detailed statistical analysis of inspection times. Data from 5 days (with 3 shifts each) was extracted from the databases containing the time spent to inspect each individual product. The total number of products in this sample was approximately 250,000 units. Figure 2.18 shows the distribution of inspection times obtained for 72 operators during 5 days. This closer look in the inspection times reveals that the variance in the distribution of inspection times is considerable. The exact average inspection time for this data is 33 s with a standard deviation of 16.7 s. 68% of the products were inspected between 20 s and 35 s but the boundaries of the distribution go further down to 5 s and a maximum of 3 min. There were also products inspected in more than 3 minutes in the original data but after verifying with the operators, these intervals (>3 minute) were assumed as being small breaks. The overall inspection time data in this sample can be better approximated by a lognormal distribution than by a normal distribution because the inspection times are slightly skewed to the left, in this case following the direction of quicker inspections (Silva et al. 2013).

Several factors can cause variations in the inspection time. Obvious aspects can be: tires of different dimensions, tires with more flash/vents than others, tires to be delivered to more demanding customers, etc. Besides this process-related variability, the further data analysis intends to explore if human-related variability also plays a significant role in these results. For this purpose data for a period of one month was collected. In this case the analysis of the average inspection time was done to each individual contrary to the general analysis plotted in Figure 2.18. Considering the process flow illustrated in Figure 2.9, the tires allocated to each individual buffer are randomly selected. For this reason, identical average inspection times would be expected for each individual, if one considers data from a period of time able to absorb the process variability mentioned before (bigger tires, etc.). Figure 2.19 shows the average inspection time for 53 operators. Substantial between-subjects variability is disclosed by the data. While some operators present an average inspection time close to 40 seconds, others do not need on average more than 25 seconds. The significant differences in individual inspection time induces also variability in the total number of parts inspected per day by each operator that subsequently affect the visual inspection overall throughput. The fact that the visual inspection is in between two automatic processes that ideally should not be blocked neither starving raises many challenges about the suitable number of operators for this process.

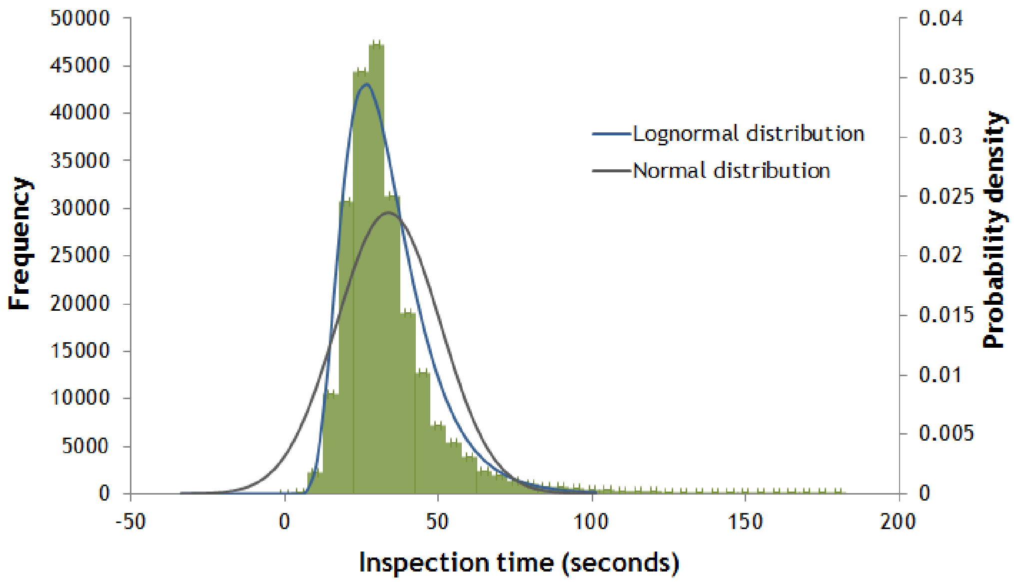


Figure 2.18 – Distribution of inspection times of five-day production volume.

The second aspect compared across operators is the rejection rate which is related to criteria used to assign a tire a non-conforming quality condition. Once more, the randomly distribution of tires would suggest that an equivalent rejection rate between operators would be obtained. Even though, the lowest part of Figure 2.19 shows that this is not the case. With an overall rejection rate close to 10%, some operators reject on average 15% of products while others in the same period of time present a rejection rate of 5% or even less. There is not an obvious relation between these two indicators: inspection time and rejection criteria. A plausible hypothesis could be that the operators taking longer to inspect would identify more NCs and thus present a higher rejection rate. If this may be the case for one operator with average inspection time of 37 seconds and rejection rate 15%, other cases contradict this hypothesis like the operator that inspects at a 25 seconds average and rejects 15%. Digging into this subject is only possible if the analysis goes beyond statistical data to shop floor observations and direct interactions with the inspectors.

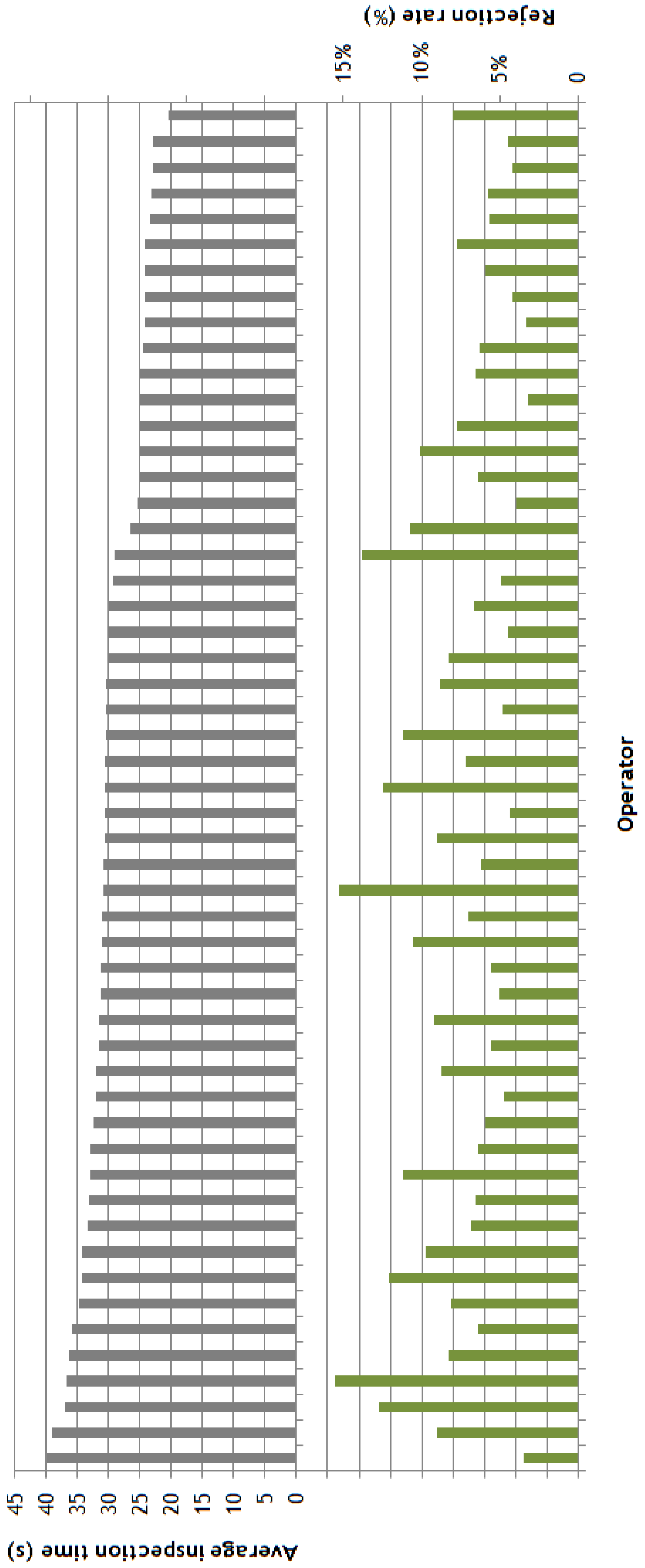


Figure 2.19 - Average inspection time and average rejection rate plotted individually to 53 operators. Average data calculated for a period of one month.

Over 60 days, participant-observations were done in the visual inspection area. Introducing the researcher in a peer-to-peer informal manner substantially contributed to more naturalistic observations. The researcher was introduced as internal collaborator of the organization with the responsibility of studying in detail the visual inspection process for later definition of improvement strategies. The initial curiosity demonstrated by the researcher together with the availability to undergo the same training as novices helped the operators to feel comfortable in the presence of the researcher. Although the researcher participated in inspection training, the researcher did not experience formal responsibility for inspection decisions. Nevertheless the participation in the training significantly contributed to a higher level of immersion in the context.

As reported by Woodcock (2014) ''hanging out'' or ''prolonged engagement'' enables the researcher to acquire the vocabulary of the domain, establish reciprocity, demonstrate trustworthiness, and build rapport. In fact the participant-observations allowed a deep understanding of the inspection process including aspects such as difficulties, pressures, errors, process adaptations, etc. All these undocumented aspects can be of extreme importance in the subsequent task of redesigning the inspection process.

From the standard procedures and quality criteria described before, the main questions to be answer with these participant-observations included:

- What are the mechanisms of visual search in a rotating object?
- How can the operators deal with the metric criteria without measuring tools?
- How can the operators memorize the rejection criteria of 76 NC codes?
- How can the operators manage multiple simultaneous tasks?
- What are the main contributors to the variability in inspection time and rejection rate?

Comparing observations against the standard procedures allowed for a straightforward conclusion in agreement with Dekker (2006). Several mismatches between written procedures and operational practice exist. Different inspectors use different approaches and adapt methods under the same circumstances, depending on each individual experience, knowledge, and confidence level.

Some examples of these individual adaptations are the fact that some operators cut flash at first and repeat the rotational cycle for inspecting the tire while other seem to be able to perform both actions simultaneously. Another example is related with the use of touch. Some operators touch the inner liner of the tire because they found relevant the addition of haptic sensorial information. On the other hand other operators trust exclusively in their sight capabilities.

Although the guidelines provided by the organization highlight the importance of finishing the inspection of the whole tire even if an imperfection was already detected beforehand, some operators reject the tire immediately. This may contribute to a faster inspection of non-conforming items.

Despite the individual adaptation of the methods, all observed inspectors reveal an impressive sense of responsibility and astonishing detection capabilities. Some imperfections do not have a significant visual manifestation. Sometimes it is only a slight shadow in a curved region of the tire imperceptible to novices or to the researcher, even when told about its location.

The most visible and coarse imperfections are immediately identified in a preattentive moment by the operator. This typically occurs right before the start of the machine rotational cycle when the operator performs a rapid global observation. The great majority of cases are out of this scenario either for being OK products or for containing minor imperfections not visible at first glance. Most operators agree that in these cases the rotation of the tire assists in the detection of imperfections. They usually say that inspecting a tire is not a matter of finding imperfections. Instead they say that the "imperfections are brought to us". The movement seems to help in the detection process since any unexpected artifact will pop up of the usual constant grey color of the tire. This strategy also minimizes the eye movement necessary. The operators typical fixate a point and wait for the tire to rotate. An imperfection is usually evidenced as a sudden shadow or brightness. This is the reason why many operators state that their performance is best when the tires come directly from the vulcanization area to the visual inspection because of the vibrant grey color deprived of dust. The successive darker color acquired with time increases the difficulty in detection.

Experienced operators perform inspection with smoothness and speed applying advanced know-how and a repertoire of heuristics. Heuristics enable associations such as: a certain tire article tends to contain a certain imperfection in a specific location. The visual search is then oriented not only but with more care to that particular location. These know-how rules can be as detailed as the example of taking into consideration the final customer of a certain tire and adjust the criteria according to the requirements and recent complains of each. This rule-based behavior evolves through an adaptation process in which slips are inevitable side effects of the exploration of the boundaries of acceptable criteria. For the adjustment of these boundaries an additional specialized operator called overinspector re-inspects a random sample of tires after being validated as conforming by the inspectors. Besides avoiding that some non-conforming tires are delivered to the customer, the overinspector also plays an important role in alerting the inspectors of misses and in requesting adaptation of the rejection criteria.

These known-how rules are significantly influenced by the level of confidence of the operator, culture of the group and strategies defined by the organization and can justify some of the variability encountered in rejection rates and inspection times. An example of these individual differences was captured in an informal conversation with one operator that explained that a particular tire had an imperfection, which made arguable the quality acceptance level. He told "the majority of my colleagues would reject this tire but I know that this decision will just overload the grader because he will validate the tire as OK". Experience and knowledge may reduce these individual differences but intrinsically there are individuals more confident or risk-averse.

The continuous learning and evolvement of expertise and advanced know-how, together with some external factors and stochastic variability can result in errors in the inspection process. All errors involve some kind of process deviation. Errors in this case can occur from not following the standard procedures or the quality assessment. Table 2.3 lists the most frequent errors that can occur in the inspection process organized by task function (search, decision, respond) and classified by its consequence. All of these errors occurred during shop floor observations. The list also suggests causality although it does not intend to make an exhaustive identification of all possible causes of error. Rather the idea is to develop the consciousness of these errors and a perception of the main causes for the future attempt of developing improvement or avoidance strategies.

The fact that the inspection process is very repetitive, in which the only changeable element is the tire under analysis, leads to some distractions and boredom that may originate an error in the procedure. These are typically called as slips or lapses and are described as failures on the execution of some routine task in familiar circumstances (Reason 2005). An example of this is error 9, misplacing the tire after inspection is correctly done. Analysing this error in the light of the error causality model proposed by Reason (2005) allows the identification of latent factors that may contribute to this error.

Table 2.3 - Generic errors in the manual inspection of tires and list of probable causes.

	Errors	Causal Factors
Search	1. Imperfection missed in tread	The indirect observations through the mirror are sometimes mentioned as inefficient
	2. Imperfection missed elsewhere	Non-searched areas, distractions, fatigue, stress, production pressures, etc.
	3. Imperfection seen while tire was rotating but lost/forgotten afterwards	There is not a prompt relation between visualizing and deciding
	4. Damage the tire while cutting flash	Distractions, simultaneous visual fixation in other tire regions for inspection, etc.
Decision	5. Defective product incorrectly classified as conforming	Ambiguous criteria, lack of training, lack of decision feedback
	6. Conforming products incorrectly rejected	
	7. Incorrect identification of the tire in the IT system	If a product is much more common than others, operators have the tendency to select that one
	8. Imperfection marked in the tire but classified as OK in the IT system	Repeated routine of pressing OK bottom since that is the case for 90% of the cases
Respond	9. Conforming product placed in the non-conforming conveyor	Distractions or blockages affecting one of the two conveyors
	10. Non-conforming product placed in the conforming conveyor	

In terms of incorrect decisions in the quality assessments, error causality can be very complex to be described. Some egregious errors can occur but the majority are misses on the "gray" and questionable zone either in the search or decision. For successful performance, operators have to navigate between two boundaries: not rejecting conforming items and not accepting non-confirming items. In the quality evaluation of tires the most critical error is the case of accepting a non-conforming item. This can occur because the operator missed the imperfection or because after visualizing it he did not apply the adequate rejection criterion. Although the output is the same, a non-conforming item approved to be delivered to the customer, the causes are different. When raising questions about what the circumstances were that may have induced these errors, several arguments can be placed. In the first case one can question if the operators have access to adequate tools to perform the visual search accurately while in the second case, the question is more oriented to the access of clear rejection rules provided by the organization.

No data is available in the company about the number of occurrences of each of the listed errors. Also, estimates are very difficult to be obtained by the researcher because there are not available tools to track these errors down in the production line. A rough guess of the errors occurring in the quality assessments can be extracted from the overinspector activities. Overinspector only verifies a limited sample of tires previously validated as conforming and for this reason the only possible error is finding non-conforming items previously ranked as conforming. At the moment there is not a formal and systematic way for the graders to inform the operators about inadequate rejections.

Assisting to the overinspector process over 12 days enabled the researcher to register the cases in which non-confirming items were validated as OK by the inspectors. Along this analysis, the operators were not questioned about their errors by the researcher. The objective was to have an estimation of the most common mistakes registering the location of the missed imperfections and cross check with the operators some possible causes. The plot shown in Figure 2.20 demonstrates that the areas where the inspectors tend to fail the most are the sidewall, bead and tread. Sidewall and bead are as described in Figure 2.16 the areas that more often contain imperfections. The higher probability of containing imperfections seems to lead to higher probability in missing those, considering that not always heuristic rules can be applied by the operators.

Very often the operators mention that the use of the mirror to inspect the tread is not very practical. The fact that the mirror gets easily dirty and is positioned in the lateral side of the machine makes its use less frequent. This may be one of the reasons why the percentage of errors in the tread is so significant.

When confronted with an error the inspectors usually agree and re-use the information in future assessments but also highlight the difficulties encountered in the inspection process.

Figure 2.21 shows a cause and effect diagram, also known as Fishbone diagram, developed with the inputs of the operators. This simple graphical technique is used to sort factors that contribute to a given situation, in this case an error in the inspection process. The causes are grouped in categories: human factors, equipment, methods and procedures, training, environment, others. Some of the causes were already mentioned before such as: the difficulty in using the mirror to verify the tread, the differences in individual confidence level, the lack of systematic feedback about the errors in quality decisions, etc.

Other causes that should be referred are the fact that the majority of the operators dislike the fact that trimming and inspection occur simultaneously. The percentage of tires that need to be trimmed is very significant (internal estimations lay around 70-85% of the cases) and is frequently mentioned as source of distractions.

Another important aspect is the lighting conditions to perform the inspection task. As mentioned before, the tire is an intricate object difficult to be inspected due to its curvature and color. Several studies have been made in order to determine the most suitable light conditions but it is inevitable that while some areas are well illuminated others are not due to the natural shape of the object.

The knowledge described along this chapter is expected to provide hints to the subsequent chapters about system redesign. Especially when reconsidering the human contribution in the process, some strategies can be defined in order to remove or at least lighten these causes and thus decreasing the probability of errors to occur.

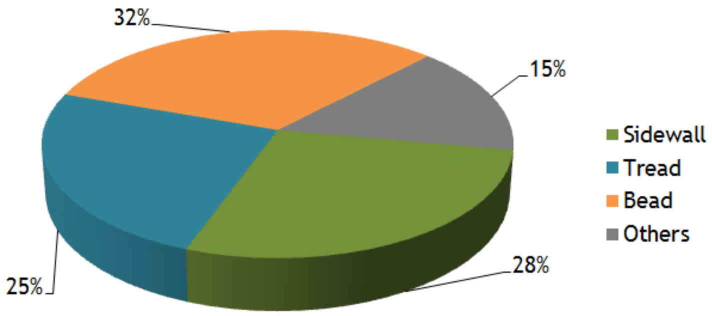


Figure 2.20 - Percentage of errors in which the operator missed the detection of an imperfection across the tire areas.

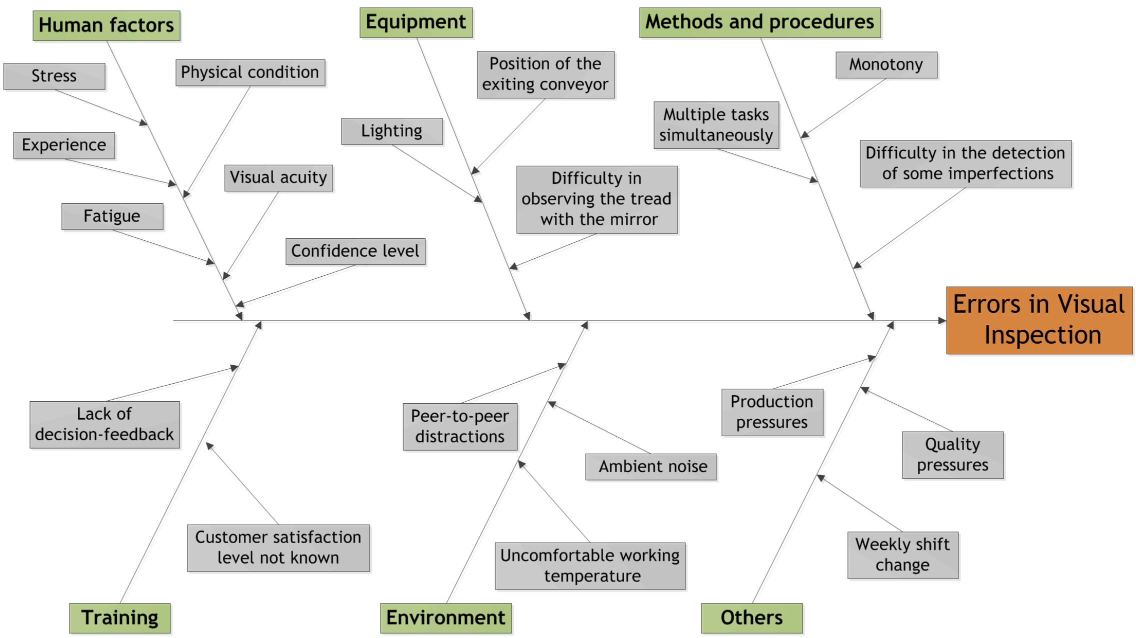


Figure 2.21 - Cause and effect diagram for errors in the visual inspection of tires.

2.5 References

Ballou, Donald P., and Harold L. Pazer. 1982. "The Impact of Inspector Fallibility on the Inspection Policy in Serial Production Systems." Management Science no. 28 (4):387-399.

Baveja, A., Colin G. Drury, Mark H. Karwan, and David M. Malon. 1996. "Derivation and test of an optimum overlapping-lobes model of visual search." Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on no. 26 (1):161-168.

Chan, A. H. S., and A. J. Courtney. 1996. Measurement of visual lobe dimensions with a simultaneous foveal task. Paper read at Systems, Man, and Cybernetics, 1996., IEEE International Conference on, 14-17 Oct 1996.

Chan, Alan H. S., and Cathy H. Y. Chiu. 2010. "Visual lobe shape characteristics of experienced industrial inspectors and inexperienced subjects." Human Factors and Ergonomics in Manufacturing & Service Industries no. 20 (5):367-377.

Chiu, Cathy H. Y., and A. H. S. Chan. 2007. Enhanced Features of VIsual LObe Measurement System (VILOMS). Paper read at International MultiConference of Engineers and Computer Scientists 2007.

Coran, Aubert. 2013. "The Science and Technology of Rubber Fourth Edition." In The Science and Technology of Rubber (Fourth Edition), edited by James E. Mark, Burak Erman and C. Michael Roland, i. Boston: Academic Press.

Dekker, Sidney. 2006. The Field Guide to Understanding Human Error. Great Britain: Ashgate Publishing Limited.

Drury, C. G. 2001. "Human Factors and Automation in Test and Inspection." In Handbook of Industrial Engineering - Technology and Operations Management, edited by Gavriel Salvendy. John Wiley & Sons.

Drury, Colin G., Kimberly M. Ghylin, and Karen Holness. 2006. "Error Analysis and Threat Magnitude for Carry-on Bag Inspection." Proceedings of the Human Factors and Ergonomics Society Annual Meeting no. 50 (11):1189-1193.

Duffuaa, S. O., and Mehmood Khan. 2005. "Impact of inspection errors on the performance measures of a general repeat inspection plan." International Journal of Production Research no. 43 (23):4945-4967.

ETRMA. 2010. Revision of the General Product Safety Directive In (2001/95/EC) edited by European Tyre & Rubber Manufacturers' Association: ETRMA.

Ghylin, K.M., C. G. Drury, and A. Schwaninger. 2006. Two-component model of security inspection: application and findings. Paper read at 16th World Congress of Ergonomics, IEA 2006, at Maastricht, The Netherlands.

Gramopadhye, Anand K., and Kartik Madhani. 2001. "Visual Search and Visual Lobe Size." Proceedings of 4th International Workshop on Visual Form.

Holmgren, John. 1968. "Visual search with imperfect recognition." Perception & Psychophysics no. 4 (4):247-252.

Hong, Seung-Kweon. 2005. "Human stopping strategies in multiple-target search." International Journal of Industrial Ergonomics no. 35 (1):1-12.

Lindemuth, B. E. . 2006. "An Overview of Tire Technology." In The Pneumatic Tire. National Highway Traffic Safety Administration.

Luck, Steven J., and Steven A. Hillyard. 1994. "Electrophysiological correlates of feature analysis during visual search." Psychophysiology no. 31 (3):291-308.

Marmaras, Nicolas, and Tom Kontogiannis. 2001. "Human Factors and Ergonomics." In Handbook of Industrial Engineering - Technology and Operations Management (3rd Edition). John Wiley & Sons.

McCarley, Jason S., Arthur F. Kramer, Christopher D. Wickens, Eric D. Vidoni, and Walter R. Boot. 2004. "Visual Skills in Airport-Security Screening." Psychological Science no. 15 (5):302-306.

Melloy, Brian J., Sourav Das, Anand K. Gramopadhye, and Andrew T. Duchowski. 2006. "A model of extended, semisystematic visual search." Human Factors no. 48 (3):540-554.

NHTSA. 2001. Tire Safety Everything Rides on it. edited by National Highway Traffic Safetty Admnistration.

Nothdurft, Hans-Christoph. 2006. "Salience and target selection in visual search." Visual Cognition no. 14 (4-8):514-542.

Rasmussen, J. 1983. "Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models." Systems, Man and Cybernetics, IEEE Transactions on no. SMC-13 (3):257-266.

Rasmussen, J. 1985. "The role of hierarchical knowledge representation in decisionmaking and system management." Systems, Man and Cybernetics, IEEE Transactions on no. SMC-15 (2):234-243.

Rasmussen, J. 1986. Information Processing and Human-Machine Interaction: An Approach to Cognitive Engineering: Elsevier Science Inc.

Reason, J. 2005. "Safety in the operating theatre – Part 2: Human error and organisational failure." Quality & Safety in Health Care no. 14:56-61.

Reason, James. 2000. "Human error: models and management." BMJ no. 320 (7237):768-770.

Scott, Derek. 1993. "Visual search in modern human-computer interfaces." Behaviour & Information Technology no. 12 (3):174-189.

Silva, E., M. Donauer, A. Azevedo, P. Peças, and E. Henriques. 2013. A Case Study Evaluating the Impact of Human Behavior on a Manufacturing Process In-line with Automatic Processes by Means of a Simulation Model. Paper read at IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), at Bangkok, Thailand.

Sylla, Cheickna, and Colin G. Drury. 1995. "Signal detection for human error correction in quality control." Computers in Industry no. 26 (2):147-159.

Wang, Mao-Jiun J., Shu-Chiang Lin, and Colin G. Drury. 1997. "Training for strategy in visual search." International Journal of Industrial Ergonomics no. 20 (2):101-108.

Wolfe, Jeremy M. 1994. "Guided Search 2.0: A Revised Model of Visual Search." Psychonomic Bulletin & Review no. 1 (2):202-238.

Wolfe, Jeremy M. 2003. "Moving towards solutions to some enduring controversies in visual search." Trends in Cognitive Sciences no. 7 (2):70-76.

Woodcock, K. 2009. "Inspecting for Safety Hazards." In Contemporary Ergonomics 2009. Taylor & Francis.

Woodcock, Kathryn. 2014. "Model of safety inspection." Safety Science no. 62 (0):145-156.

Chapter 3
Redesigning the manual inspection process of tires

As mentioned in Chapter 1, the objective of this dissertation is to develop a research strategy that leads to a significant increase in the throughput of the quality inspection process of tires in order to reduce costs. A cost breakdown analysis done in the context of this project showed that manpower is responsible for 70% of total costs in the visual inspection area. Thus, pragmatic strategies to significantly reduce costs mandatorily involve redesigning the human role so that each operator's throughput is increased. The understanding of the current inspection process, described in the previous chapter, is an important element in order to redesign the inspection process. Generally speaking two possible approaches to increase efficiency can be followed: determining automatically the quality state of a percentage of tires or the implementation of technological tools that decrease the manual inspection time per product. In both cases, the practical outcome is that the overall number of tires per operator per unit of time is increased. Many different strategies can be followed to increase process efficiency. Introducing automation and combining technological solutions and operators is the path to be considered.

Concepts of LOA and models to support decision of task allocation between human and machines are presented. Subsequently an advisable strategy is provided and a description of the suggested system is given.

3.1 Models for designing hybrid systems

The view on automation does not need to be a ''all-or-none'' decision (Parasuraman, Sheridan and Wickens 2000). Many scientific and industrial studies suggest that potential of automation is maximized when interrelated with appropriated and well-designed human tasks (Tweedale 2013). The challenge of this view is in the definition of the task allocation between human and technical systems for the accomplishment of a given task (Säfsten, Winroth and Stahre 2007). Continuous technical developments in hardware and software make it possible to automate many tasks that at once could only be performed by humans. The advances of technology means that tomorrow's automation can do more and more (Parasuraman and Wickens 2008). This does not mean that the strategy to follow should be to attempt to automate all activities that are possible to be automated, only considering the available technology and capital constraints (Mital 1995). Naively assuming that the tasks can simply be broken into independent sub-tasks and then assigned to either automation or humans may result in inefficient processes and instances of insufficient impact of automation have been reported (Parasuraman and Riley 1997; Kaber et al. 2005). Thus, the benefits anticipated by system designers when implementing automation (increased efficiency, improved safety, enhanced flexibility of operations, lower operator workload, and so on) may not always be realized (Parasuraman and Manzey 2010). Situations were reported in which the human process costs got even higher after the introduction of automated aids because of unsuccessful automatic situations where manual re-testing was needed (Rovira, McGarry and Parasuraman 2002). This is not to say that high levels of automation should not be considered. However, deciding the appropriate level of automation requires additional considerations besides cost analysis and technological feasibility, such as involvement of operators and detailed task analysis. Thus scenarios besides economic or leftover allocations (humans are responsible for whatever is not possible to be automated) should be considered.

Various design alternatives are possible and several models have been proposed regarding to what extent functions should be automated. All analyses involve multiple issues and considerations, some of them not even quantifiable. Before defining the level of automation and task allocation one has to clarify and distinguish the different possibilities.

Numerous levels and scales of automation have been proposed but for the purpose of this study, the ten-level scale originally proposed by Sheridan and Verplank (1978) will be presented, as this is a commonly referenced taxonomy (Cummings et al. 2007). Sheridan and Verplank (1978) suggested a spectrum of different degrees of automation that can be appropriately applied to different systems or problems (Sheridan 1995). The ten-level scale ranges from no automation to complete automation (Table 3.1). Lower level implies mainly manual tasks whereas a high level implies limited or no manual tasks. Indeed, from level 7 on, human can take no action.

Table 3.1 - Ten-level scale of levels of automation (adapted from Sheridan (1995)).

LOW	1 The computer offers no assistance; humans must take all decisions and actions.
	2 The computer offers a complete set of action alternatives, or
	3 Narrows the selection down to a few, or
	4 Suggests one, and
	5 Executes that suggestions of humans approve, or
	6 Allows humans a restricted time to veto before automatic execution, or
	7 Executes automatically, then necessarily informs humans, and
	8 Informs the human only if asked, or
	9 Informs the human after execution if the computer decides to.
HIGHT	10 The computer decides everything and acts autonomously, ignoring humans.

Having described the possible levels of automation, the discussion should now be at the level of task allocation. First an identification of the functions that need to be accomplished to achieve a certain goal needs to be extensively done. Subsequently, the process of task allocation refers to the design decisions that determine which functions are to be performed by human or automation (Inagaki 2003). The most famous model to do so is called MABA-MABA (what “men are better at” and what “machines are better at”) and was firstly published by Fitts (1951). That is, tasks that are performed better by machines should be automated, whereas those that humans do better should not. The author included what became known as the Fitts List, where he exposed the tasks more prone to be allocated to each contender at the time being (Table 3.2). Unfortunately, many authors identified difficulties in the implementation of these procedures to determine which functions should be automated in a system (Parasuraman, Sheridan and Wickens 2000). This is so especially because the rapid development of computer and automation revealed some limitations of Fitts List as the binary decisions of whether to automate or not became less evident. Furthermore, this model simply suggests a direct comparison between human and automation capabilities without taking proper account of the context and dependencies between sub-tasks (Harrison, Johnson and Wright 2003; Zhang, Tang and Zhang 2011).

Table 3.2 - The Fitts list (adapted from Fitts (1951)).

In 1950s men were better at:

- Detecting small amounts of visual or acoustic energy.
- Perceiving patterns of light or sound.
- Improvising and using flexible procedures.
- Store very large amounts of information for long periods and to recall relevant facts at the appropriate time.
- Reasoning inductively.
- Exercise judgment.

Machines were better at:

- Responding quickly to control signals.
- Performing repetitive and routine tasks.
- Storing information briefly, erasing it completely.
- Reasoning deductively.
- Performing many different things at once.

More recently, Parasuraman, Sheridan and Wickens (2000) provided a four-stage qualitative model that consider whether each of four functions should be automated and in what extent, including: information acquisition (1), information analysis (2), decision selection (3) and action implementation (4). Based on this model, each of these functions can be automated to differing degrees according to the previously mentioned ten-level scale proposed by Sheridan and Verplank (1978). Figure 3.1 provides a schematic of the model with two examples of systems’ configuration and level of automation. It can be extracted from the schematic that System (A) has moderate to high acquisition automation, low analysis automation, low decision automation, and low action automation. Another system (B), on the other hand, has high levels of automation across all four dimensions more predominantly in the stage of information analysis.

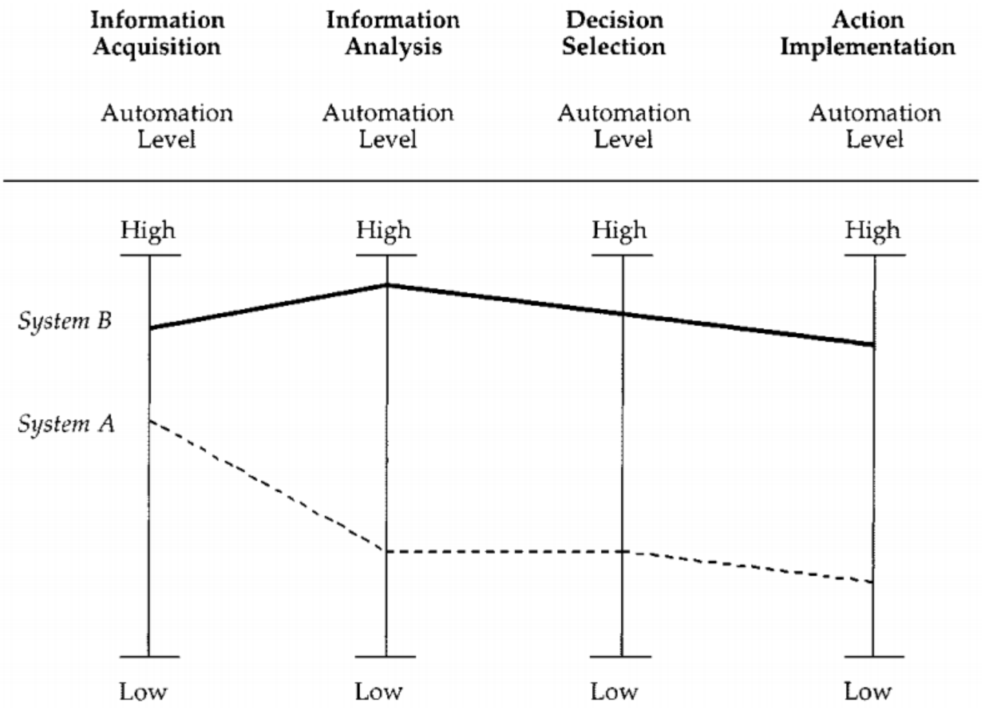


Figure 3.1 – Examples of systems with different levels of automation across the four classes of functions: information acquisition, information analysis, decision and action selection, and action implementation (adapted from Parasuraman, Sheridan and Wickens (2000)).

The first stage suggested by Parasuraman is information acquisition (1) which refers to the sensing and registration of inputs. At this stage, when the LOA is set at the lowest, human must collect every piece of information at all instances. When some automation is applied to information analysis (2) automation is able to process raw data to facilitate human interpretation. The introduction of automation in these two first stages of the model may allow that certain types of acquired information is highlighted or filtered to attract human attention. For example, some flight-booking websites currently provide a high LOA for information acquisition (1) – searching across multiple airlines and other Web sites – and also perform some information analysis (2) such as sorting flights by their cost, selecting preferable airport and proximity to desired departure times (Miller and Parasuraman 2007).

The third stage, decision selection (3), involves selection from among alternatives. The involvement of automation at this stage can vary from recommending courses of action to those that execute those courses. Action implementation (4) is the final step and refers to the actual execution of the choice (Parasuraman, Sheridan and Wickens 2000). In the example of the flight-book websites, none currently provides specific recommendations, much less actually executes (autonomously) the ticket purchase, although these capabilities are easily envisioned and technologically feasible.

Determining the level of automation that should be applied to each of the stages may not be straightforward. The authors suggest the four-stage qualitative model as a guiding framework that can help in identifying tradeoffs. The recommendable level of automation should not be seen as a static decision but rather an upper reference bound, i.e., the maximum level of automation beyond which some drawbacks may be encountered. The evaluation of a certain system design is made by examining the consequences in terms of: human performance, ease of technological development and integration, automation reliability and costs. The authors also refer the importance of evaluating the system following an iterative and dynamic procedure in which the level of automation can be adjusted according to some context indicators or further developments (Parasuraman, Sheridan and Wickens 2000). In fact, avoiding static systems and dynamically changing allocation of functions, commonly called Adaptive Automation, is strongly emerging within the automotive industry (Säfsten, Winroth and Stahre 2007). Unlike MABA-MABA model in which the tasks were strictly allocated to only one performer (human or automation), Parasuraman's model together with the notion of adaptive allocation enables scenarios in which either human or automation could perform a task acceptably. Considering that human performance degrades as time passes as a result psychological and physiological conditions, it may be wise to reallocate functions from time to time (Inagaki 2003).

The goal of this section is not to debate all methods available in the literature to optimize human-automation function allocation, which would take us far afield from the main focus of this dissertation. Rather, a more pragmatic approach that considers Parasuraman's model to structure some automation design options accounting for human intervention applied to a field study in tire industry is selected. Parasuraman's model was considered for being widely used and generic enough to be applied across industries (Oxstrand et al. 2013). Other studies propose alternative or expanded methods for task allocation but they were not explored in this document for having similar concepts and frameworks. Furthermore, across these multiple studies, there appears to be a general consensus that intermediate levels of automation should be considered (Lin, Yenn and Yang 2010; Endsley 1999).

3.2 Tire inspection functions that may be automated

In critical and risky industrial processes (such as safety or quality control), optimizations should take place but more careful and thorough investigations should be done in the introduction of automated systems. In these cases, there might be advantages in somehow keeping humans "in the loop" (Grote et al. 1995). Given this situation, it is logical to explore the potential benefits of pairing humans and automation. It is worthwhile noting that human and machine collaboration in inspection is presently being used in the medical field in critical diagnostic decisions. Computerized diagnosis inspection devices are being used by physicians. Even though, there is very few research published about inspection systems designed to use a combination of human and machine in industrial tasks (Sylla 2002; Hou and And Drury 1993). The majority of human-automation collaborations in industry occur mostly in the robotics area applied to: object handling, object transfer, assembly and welding (Brogårdh 2007; Wang, Schmidt and Nee 2013).

The inspection process of tires seems to be one case in which the introduction of automation could greatly benefit system's performance. To support this one can consider the percentage of time that the operator is doing additional activities besides inspection. Yet, for being a safety product, automation can greatly compromise company's image to the customers in case of failure. The significant human cognitive capabilities that the inspection process of tires demands from highly specialized operators, raises the challenge of how to increase efficiency by the introducing automation. Humans have shown the ability to: visually detect minor and extremely variable types of defects; apply rejection criteria in a dynamic manner based on historical information and customer specific requirements; optimize visual search by recalling information about trends of imperfections. All of these capabilities are essential for the organization to keep flexibility and improved performance.

The starting point to analyze possible improvements is task analysis aiming at splitting the overall task in subtasks. Automation may be applied at different level to every subtask constituting the parent task. Considering the standard procedure for inspection described in Chapter 2, the inspection process of tires can be summarized as listed in Table 3.3. In the scope of this research, trimming will not be considered as part of the functions to be improved. Unlike many imperfections, the origin of flash and vents is known and the research team together with the industrial partner decided to evaluate possibilities of minimizing its occurrence in the vulcanization area rather than intensifying the technological level or human cost for its cut.

Table 3.3 - Main tasks in the manual inspection process of tires

1	First cycle of visual search – if non-confirming, mark imperfections in the tire.
2	Handling the tire to prepare for second cycle.
3	Second cycle of visual search – if non-confirming, mark imperfections in the tire.
4	Assign tire identification in the Information System.
5	Associate quality decision in the Information System.
6	Releasing the tire to one of the two exit conveyors.

In terms of information acquisition (1), the lowest LOA is as today, in which the operator visually searches the entire tire to identify the relevant information for the subsequent quality decision. The possible improvement in this level is to use machine vision technologies to perform the scanning of the tire surface. The parallelism between human visual search and scanning capabilities of machine vision sensors has been extensively explored in the literature and is in the basis of the development of fully automated inspection systems in many industries. It is now almost rare to find a manufacturing plant that does not employ some form of machine vision to inspect, grade or measure.

The fact that the inspectors expressed difficulties in observing all tire surfaces and some errors occur because of inappropriate observing conditions, suggest some possible benefits of using machine vision sensors. From the human working position and vision perspective, the curved shape of the tire completely inhibits the visual access to some surfaces, and also makes it difficult for lighting conditions to be appropriate and uniform everywhere. Alternatively, recent advances in vision sensors enable high-resolution and high-speed acquisitions to be performed by successively smaller devices. Although the need for appropriate illumination persists, the possibilities of placing multiple cameras with several light sources, each of them adequately positioned according to the tire surface, might be advantageous.

Automating the information acquisition (1) stage implies that vision sensors replace the human eye as the primary information acquisition instrument but the resulting information can still be transferred to the operator for the information analysis step (2). In fact we propose that the acquired digital images should later be used by operators to perform inspection in a CAI environment instead of the current setting. The potential advantages of a CAI go beyond the improvement of the visualization conditions and can also contribute to the elimination of the time-consuming and physically demanding manual handling of the heavy and large object.

In the inspection process of tires high levels of information acquisition (1) automation can be pursued and implemented by means of machine vision technologies, if the resulting system is shown to be reliable. In this context, this means that the operators would need to be able to identify all possible imperfections digitally by visually searching the images.

In terms of information analysis (2), increases in automation level could be made by implementing image processing techniques to suggest potential defective regions to operators. As mentioned before, in a production day the typical percentage of defective tires is 9%. This means that 91% of the tires checked by the operators are OK. Moreover, from the 9% non-confirming products, the area of the imperfection is typically minimal comparing to the total area of the tire. Thus, the great majority of time, the operator is analyzing conforming regions of tires. Using image processing techniques to highlight suspicious areas may improve operators' effectiveness (reduce misses due to distractions) and efficiency (improve throughput because of quicker assessments). Instead of navigating across the whole tire area without any cue, the operator search path could be optimized by firstly check probable non-conforming areas and then the remaining area. Some studies made in the aviation area, shown that cockpit automatic traffic displays have decreased the pilot workload while improving the hazard detection performance. On the other hand, some studies mentioned the effect of over-trust or complacency (Leveson and Palmer 1997; Galster et al. 2001). It has been reported that operators pay less attention to uncued areas even when told that the cue mechanism was not perfectly reliable and for that reason, access to the raw data was still given (Parasuraman, Sheridan and Wickens 2000). In case the algorithms highlight some information reliably but not perfectly, this may lead to unattended areas.

In a higher level of automation, techniques analogous to highlighting could be used to filter information. In this case some regions of the tire would be digitally checked by the operators, while others would be solely assessed by image processing algorithms. Higher level of optimization might be achieved with this strategy but the demand for reliable automation is also much higher. Ensuring high reliability is a critical criterion when deploying these techniques as stand-alone quality assessment method. Filtering information in this context means that the decision of the quality state of some areas of the tire is entirely done by automated techniques. Therefore, not only information analysis (2) is being done automatically but also partial decision selection (3). Focusing the operator in the more ambiguous and important decisions while undoubted confirming or non-confirming areas are verified automatically might lead to maximum efficiency improvement. If the reliability tests of automation are systematically and iteratively done with successful results, the quality decision of a certain tire might be done entirely automatically. Even though, depending on the context, having a human in charge for the “final authority” might be wise because it might increase confidence levels of both organization and customers. Deciding on the quality state of a tire is a high risk task and for that reason both automated and human contributions are being considered. On the other hand, tire identification is intrinsically a very repetitive and low risk decision which makes it a strong candidate for high-level automation. The fact that it is so repetitive makes it more prone to human errors and more likely to be successfully automated. Furthermore, the dependency between tire identification and quality inspection is not significant and for this reason independent allocations may be considered.

Task number 5 in the list presented in Table 3.3 would implicitly be done automatically because of the change to a digital environment. This is advantageous compared to the current inspection process, which does not have a prompt relation between visualizing, deciding and introducing the decision in the information system, leading to potential information losses in between steps. In the CAI, the operator visualizes an imperfection, immediately draws a box containing its outside contours and automatically the tire is classified as NOK in the information system. The subsequent sub-task (number 6 in Table 3.3) would also be done automatically. Independently of being a human or computer-based decision, the tire would automatically be sent to the correct conveyor according to the decision introduced in the information system without further human intervention.

Figure 3.2 summarizes the possible scenarios for automation levels across the four-stages: information acquisition (1), information analysis (2), decision selection (3), and action implementation (4), applied to the inspection process (tire identification is not illustrated for being an independent process).In sum, high levels of information acquisition automation can be pursued and implemented if machine vision sensors are shown to be reliable in acquiring images containing all possible imperfections. The evaluation criteria should include: the impact on human detection capabilities, time needed for technological implementation and costs. Intermediate LOA and combined scenarios between machine and human vision might arise if the machine vision sensors are not successful at acquiring images of parts of the tire, such as the inner liner, as an example. In this case humans would still need to manually search that area. Higher levels of automation in information analysis (2) and decision selection (3) will mostly depend on automation reliability and development time. Action implementation (4) is expected to be reach a high LOA because it mainly implies the physical placement of tires according to the quality decision.

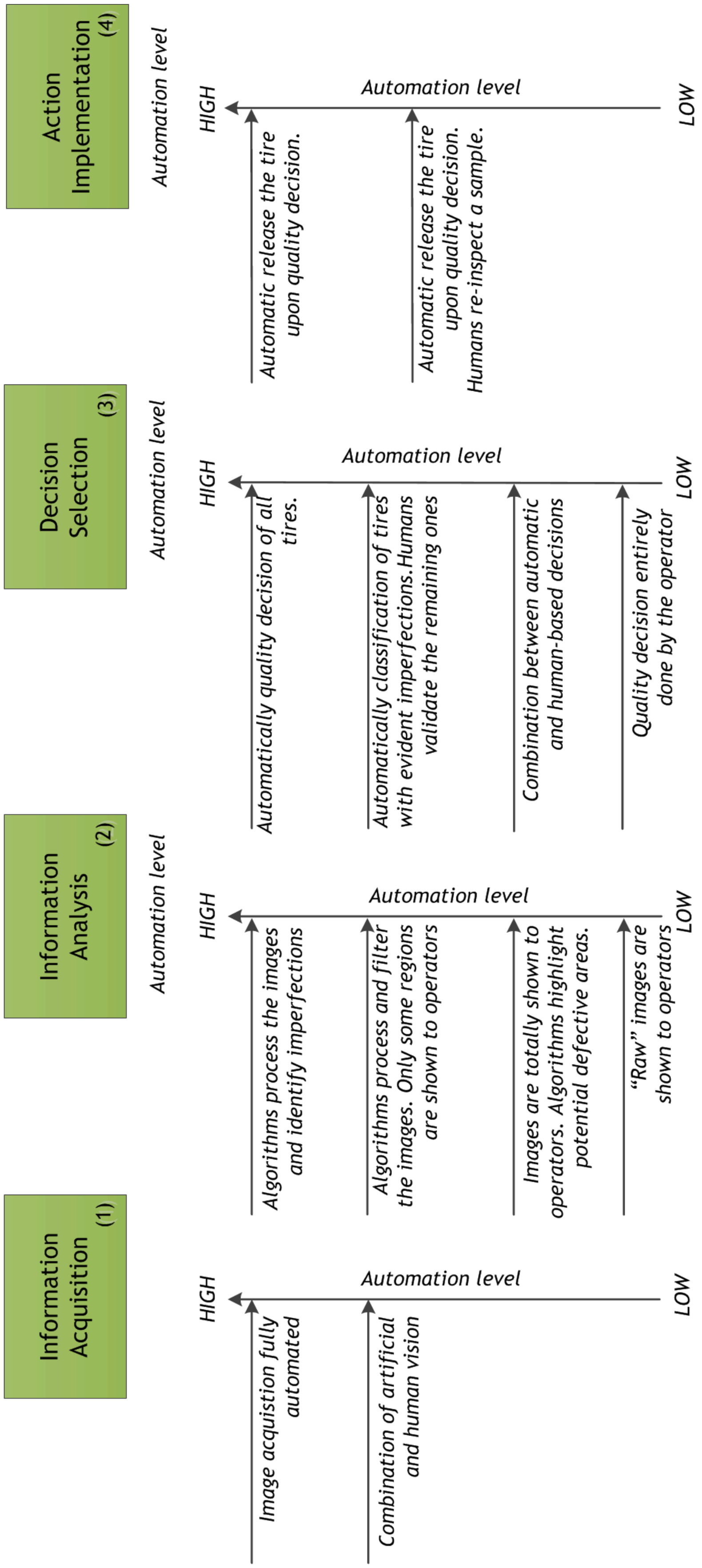


Figure 3.2 - Possible types and levels of automation for future inspection process of tires

3.3 Proposed system design

The detailed study of the current manual inspection process of tires (described in Chapter 2) complemented with the possible LOA mentioned along this chapter, resulted in inputs into the process redesign. The main outcomes of the previous analyses suggest that automation can indeed support the inspectors and allow a further level of optimization. For many reasons discussed before, the proposed system, at least at its initial phases, retains operators' contribution but their performance may be optimized by means of automated aids. Along this section, a brief description of the proposed solution will be given and in the subsequent chapters, a detailed analysis of each sub-component will be done together with the validation strategy.

The process flow illustrated in Figure 2.8 is suggested to be changed to the one shown in Figure 3.3. The scope of this research is restricted to the visual inspection process and this process is subjected to major modifications. Even though, changes in the visual inspection process can have consequences in the upstream and downstream process steps. The fact that trimming will be done apart from the visual inspection adds a process step immediately before visual inspection. The result of the efforts done by the organization to reduce the occurrence of flash and vents will dictate the most appropriate way to deal with this aspect. Nevertheless, trimming will not be discussed along this research.

The proposed visual inspection process initiates in a mechanical system equipped with machine vision technologies. Similar to the current machine for manual inspection, this new station rotates the tire so that a set of cameras can capture images along its surfaces. The cameras are placed so that all surfaces are scanned in similar conditions. At this stage, tires cannot contain flash or vents, as this may create abnormal artifacts in the images.

After the acquisition is done, the tires are collected to a buffer pool, while the images are analyzed by two image processing applications and visualized by the operators, if needed. The image processing sub-processes firstly aim at identifying the tire and then performing an automatic quality assessment. In case the automatic quality assessment is not conclusive because the software is not capable of determining the conforming level of the tire, the images (or parts of them) are sent to the CAI sub-process. One or more inspectors will observe the images and take the final decision. The tires will be released from the buffer when a final decision is inserted in the information system. Non-conforming tires will be directed to the grader, while confirming ones will be sent to the uniformity tests.

With this process redesign, the graders will receive tires for various reasons:

- Not successfully identified – a quality decision cannot be assigned to a non-identifiable item;
- Non-confirming items based on automatic quality assessment;
- Non-confirming items based on CAI quality assessment.

Even if an increase of tires sent to graders might occur, the automatic availability of the reason for rejection in the information system might be a significant advantage. In fact, one of the major expected contributions of the proposed system is enlarging the access to online information and tracking of quality issues. Nowadays the detection of a severe imperfection triggers the following procedure: the inspector rejects the tire and sends it to the grader.

The grader searches for the colored wax mark done by the inspector and evaluate its severity. In situations in which some corrective actions should immediately be applied, the grader calls the Quality Department and someone responsible comes and re-evaluate the tire. The graders commented that sometimes this process is long and by the time the corrective actions take place, many other tires were already produced with the same problem.

The introduction in the manufacturing process of digital images of tires together with the fact that all software applications are reading and writing to a centralized database enables that the abovementioned process is modified to: the tire being scanned and then automatically inspected. In case the automatic inspection is not conclusive, the image is inspected by the specialized operators, who will mark the region of the imperfection in the image display application. The tire will be sent to graders that will also have access to an application to visualize the marked image by the operator. In case corrective actions are needed, the images are immediately sent to the Quality Department that can use them to stop the process that needs to be corrected. This intends to be just one example of the many possible benefits of digitalizing tires, as a ground based strategy to optimize the visual inspection process but also improve the communication and tracking capabilities in the entire manufacturing process.

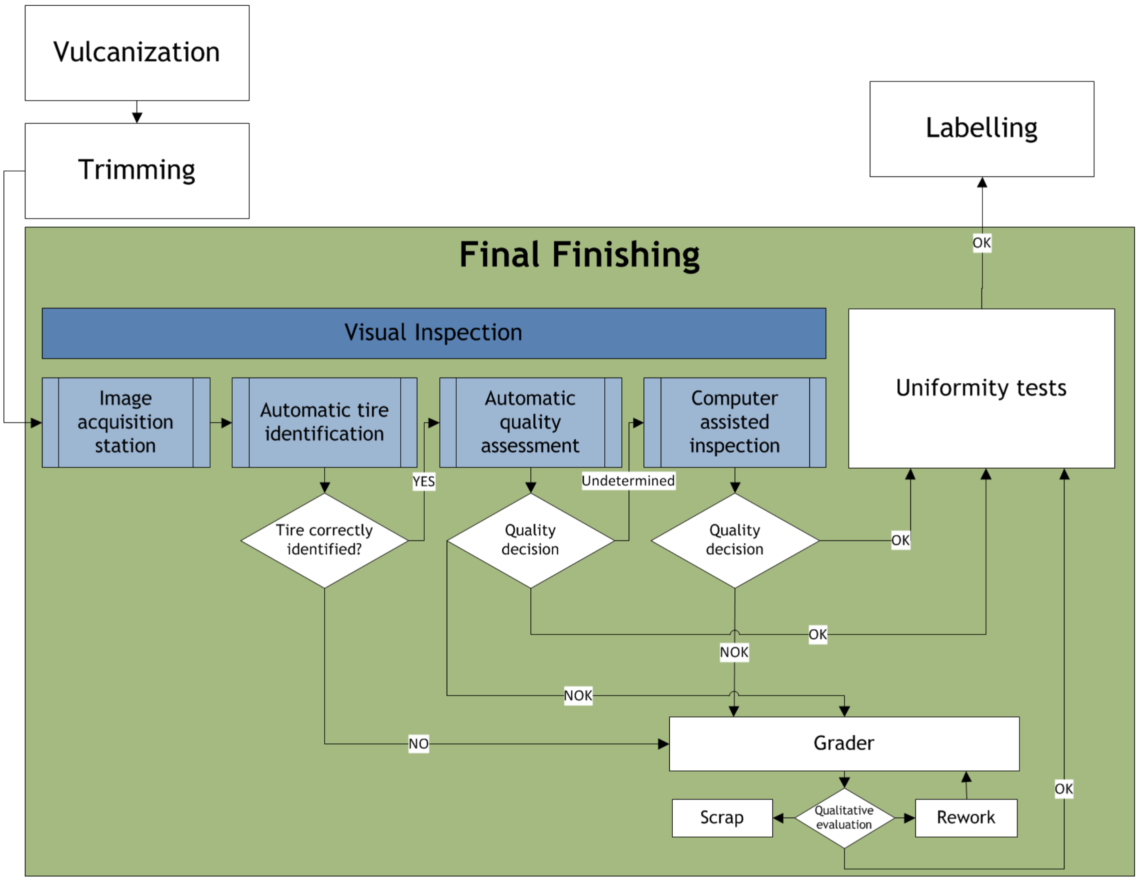


Figure 3.3 - Diagram illustrating the proposed process flow in the Final Finishing area

The overall attempt towards this system redesign (Figure 3.3) is to conceive an efficient process able to deal with the complexities intrinsic to the inspection task is a sustainable and flexible manner. This goal can be attained with the combination between automated solutions and human capabilities. Furthermore, the relation between these two cooperating agents is suggested to evolve with time according to improvements in automation reliability, human-computer interfaces, customer requirements, internal strategies, new products, etc. Several internal feedback loops were designed so that the image acquisition conditions can be improved by operators' feedback, while automatic detection algorithms can evolve according to operators' decision, whose performance can also be improved by continuous developments in interfaces and suitable automated aids. Describing each of these components will be done in the next chapters, aiming at demonstrating that human inspectors and machine vision systems have better performance than either humans alone or machine vision systems alone.

An incremental validation and implementation methodology is suggested to help the organization to move smoothly in the direction of the proposed process redesign.

3.4 References

Brogårdh, Torgny. 2007. "Present and future robot control development—An industrial perspective." Annual Reviews in Control no. 31 (1):69-79.

Cummings, M.L., S. Bruni, S. Mercier, and P.J. Mitchell. 2007. "Automation Architecture for Single Operator, Multiple UAV Command and Control." The International C2 Journal no. 1 (2).

Endsley, Mica R. 1999. "Level of automation effects on performance, situation awareness and workload in a dynamic control task." Ergonomics no. 42 (3):462-492.

Fitts, Paul M. ; Viteles, M. S. ; Barr, N. L. ; Brimhall, D. R. ; Finch, Glen ; Gardner, Eric ; Grether, W. F. ; Kellum, W. E. ; Stevens, S. S. 1951. Human engineering for an effective air-navigation and traffic-control system. edited by Ohio State University.

Galster, Scott M., Jacqueline A. Duley, Anthony J. Masalonis, and Raja Parasuraman. 2001. "Air Traffic Controller Performance and Workload Under Mature Free Flight: Conflict Detection and Resolution of Aircraft Self-Separation." The International Journal of Aviation Psychology no. 11 (1):71-93.

Grote, G., S. Weik, T. Wäfler, and M. Zölch. 1995. "Criteria for the complementary allocation of functions in automated work systems and their use in simultaneous engineering projects." International Journal of Industrial Ergonomics no. 16 (4-6):367-382.

Harrison, M. D. , P. D. Johnson, and P.C. Wright. 2003. "Relating the automation of functions in multi-agent control systems to a system engineering representation." In Handbook of Cognitive Task Design, edited by Lawrence Erlbaum Associates, 503-524.

Hou, Tung-Hsu, and Li Lin Colin G. And Drury. 1993. "An empirical study of hybrid inspection systems and allocation of inspection functions." International Journal of Human Factors in Manufacturing no. 3 (4):351-367.

Inagaki, Toshiyuki. 2003. "Adaptive Automation: Sharing and Trading of Control." In Handbook of Cognitive Task Design, edited by Erik Hollnagel, 147-169.

Kaber, David B., Melanie C. Wright, Lawrence J. Prinzel, and Michael P. Clamann. 2005. "Adaptive Automation of Human-Machine System Information-Processing Functions." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 47 (4):730-741.

Leveson, Nancy G. , and Everett Palmer. 1997. "Designing Automation to Reduce Operator Errors ".

Lin, Chiuhsiang Joe, Tzu-Chung Yenn, and Chih-Wei Yang. 2010. "Optimizing human-system interface automation design based on a skill-rule-knowledge framework." Nuclear Engineering and Design no. 240 (7):1897-1905.

Miller, Christopher A., and Raja Parasuraman. 2007. "Designing for Flexible Interaction Between Humans and Automation: Delegation Interfaces for Supervisory Control." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 49 (1):57-75.

Mital, Anil. 1995. "The role of ergonomics in designing for manufacturability and humans in general in advanced manufacturing technology: Preparing the American workforce for global competition beyond the year 2000." International Journal of Industrial Ergonomics no. 15 (2):129-135.

Oxstrand, Johanna , John O'Hara, Jeffrey C. Joe, and Kat. 2013. Development of an Initial Model of Human-Automation Collaboration

Parasuraman, R., T. B. Sheridan, and Christopher D. Wickens. 2000. "A model for types and levels of human interaction with automation." Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on no. 30 (3):286-297.

Parasuraman, Raja, and Dietrich H. Manzey. 2010. "Complacency and Bias in Human Use of Automation: An Attentional Integration." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 52 (3):381-410.

Parasuraman, Raja, and Victor Riley. 1997. "Humans and Automation: Use, Misuse, Disuse, Abuse." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 39 (2):230-253.

Parasuraman, Raja, and Christopher D. Wickens. 2008. "Humans: Still Vital After All These Years of Automation." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 50 (3):511-520.

Rovira, Ericka, Kathleen McGarry, and Raja Parasuraman. 2002. "EFFECTS OF UNRELIABLE AUTOMATION ON DECISION MAKING IN COMMAND AND CONTROL." Proceedings of the Human Factors and Ergonomics Society Annual Meeting no. 46 (3):428-432.

Säfsten, K., M. Winroth, and J. Stahre. 2007. "The content and process of automation strategies." International Journal of Production Economics no. 110 (1–2):25-38.

Sheridan, T. . 1995. Human centered automation: oxymoron or common sense? . In IEEE International Conference on Systems Man and Cybernetics. Vancouver, BC.

Sheridan, Thomas B., and William L. Verplank. 1978. Human and Computer Control of Undersea Teleoperators. edited by Man-Machine Systems Lab - MIT. Cambridge, MA.

Sylla, Cheickna. 2002. "Experimental investigation of human and machine-vision arrangements in inspection tasks." Control Engineering Practice no. 10 (3):347-361.

Tweedale, Jeffrey W. 2013. "Using Multi-agent Systems to Pursue Autonomy with Automated Components." Procedia Computer Science no. 22 (0):1369-1378.

Wang, Lihui, Bernard Schmidt, and Andrew Y. C. Nee. 2013. "Vision-guided active collision avoidance for human-robot collaborations." Manufacturing Letters no. 1 (1):5-8.

Zhang, An, Zhili Tang, and Chao Zhang. 2011. "Man-machine Function Allocation Based on Uncertain Linguistic Multiple Attribute Decision Making." Chinese Journal of Aeronautics no. 24 (6):816-822.

Chapter 4

Machine vision system for imaging acquisition of tires

Developing a successful machine vision system depends on the complementarity and integration of its sub-components, usually recalling many knowledge domains. Aspects such as mechanical systems, vision sensors, optics, lighting, electronics, integration software, and image processing techniques are typically necessary. Figure 4.1 illustrates a generalized sequence of the major aspects to be decided in the development of a machine vision system.

The application domain, the nature of the task to be accomplished and the environment will determine the requirements for each component of the system. Only once the requirements of a particular application are specified, then appropriate decisions for the design and development of the system can be taken, as well as the selection of the appropriate machine vision software and hardware.

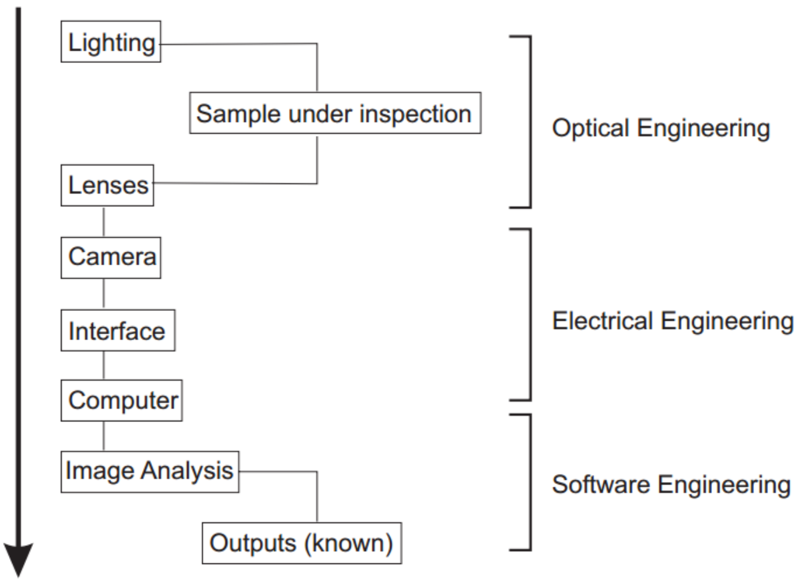


Figure 4.1 – Information chain and knowledge domains in an machine vision system (adapted from Hornberg (2006)).

The inspection process is proposed to be redesigned following Figure 3.3 which is recalled in a simplified version in Figure 4.2. This chapter will focus on the first component of the renewed inspection process: Image Acquisition Station (in green in Figure 4.2). In the context of this research, the development of the machine vision system begins with the understanding of the tire application's requirements and constraints, most of which were already mentioned in this document. Before considering manufacturing requirements such as cycle times, space required, costs and maintenance, this chapter will focus on feasibility and reliability aspects of the visual system. Evaluating if a machine vision system can have a comparable performance to the human eye acquisition, when it comes to accurately capture imperfections in tires, is the main research question addressed by this chapter.

The machine vision system was materialized as an industrial prototype for image acquisition. Although not inserted in the production line, the prototype was installed in the manufacturing plan as a side cell. Several optimizations were made possible due to the proximity to the production line. The image acquisition station encloses a mechanical system that rotates one tire at a time, while a set of fixed cameras scan its surfaces in proper lighting conditions. The significant variability in tire sizes (rim, tread width, sidewall height) leads to the need for mechanical adjustments in the structure and the reposition of the lighting systems accordingly to the tire being tested.

This chapter will briefly describe the mechanical structure and fully characterize the vision system. The relative position between the vision sensors and lighting was specially studied for the tire application, accounting for its deformable material, color and shape. Capturing the enormous variety of imperfections will significantly depend on the lighting system and its placement. Configurations are defined attempting to create areas of contrast, brightness, shadows and reflexes.

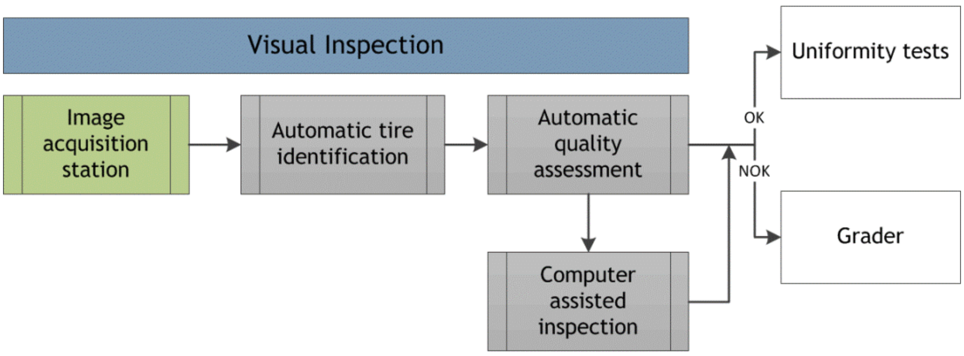


Figure 4.2 - Decomposition of the proposed inspection process of tires.

4.1 Overview of industrial machine vision applications

It is very difficult to provide a completely satisfactory definition of machine vision. Generally speaking it is a technology intensive field, in which a diversified range of technologies and engineering domains are integrated in order to: "allow a computer to understand aspects of its environment using information provided by visual sensors" (Liu and MacGregor 2005).

Several tasks need to be accomplished by the machine vision system such as: image acquisition, image processing, and decision making. The role of the image-acquisition sub-system in a machine vision system is to acquired images by means of optical noncontact sensors and transform the optical image data into an array of numerical data (Golnabi and Asadpour 2007). This sub-system will be the focus of this chapter.

The hardware structure of a typical image-acquisition system typically includes: one or more cameras placed at the scene under inspection, illumination and a computer that will process the images acquired. In industrial applications, image-acquisition systems typically sense the surface of an object on a moving conveyor to determine its quality condition (Figure 4.3).

Over the last 20 years, machine vision has taken a vital role in the control of industrial processes. Automated visual inspection in the industrial context is used to segregate non-conforming items and as means of gathering statistical information to provide feedback to the manufacturing process (Thomas et al. 1995). In this area, machine vision has been reported to be a rapid, economic, consistent and non-destructive inspection technique and, for those reasons, expansion to diverse industries continues to occur. The continuous development of machine vision technologies allows that speed and accuracy satisfy ever-increasing industries requirements, aspect that contributes to the development of several totally automated processes (Brosnan and Sun 2002). In fact, most industries are following the trend of implementing fully automated inspection systems rather than using machine vision systems to assist inspectors. Most common arguments in favor of this strategy include: the fact of being tireless, having low operating costs, and being relatively free of random errors such as the ones caused by human factors (Thomas et al. 1995).

Independent of the decision making process (automatic or human-based), the machine vision system firstly needs to be effective in the capture of image that will later be analyzed and interpreted. The requirements for the design and development of a successful machine vision system in industry significantly vary depending on the application domain. Aspects such as: industrial environment and context, product characteristics, inspection requirements and available technologies, need to be considered because each of them restricts and interacts with the other (Malamasa et al. 2003).

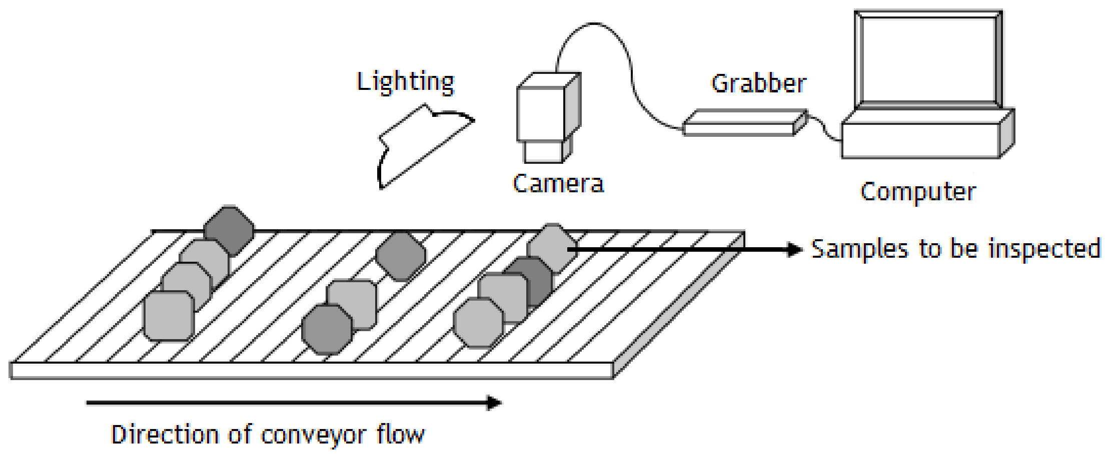


Figure 4.3 - Components of an industrial machine vision system (adapted from Al-Mallahi et al. (2010)).

The variability in system requirements led to the development of image-acquisition systems with significant differences in hardware selection and operational mode. Table 4.1 lists some examples of machine vision systems grouped by inspection objective and categorized by application field. The inspection objective maybe classified as: superficial (whether or not the surface contains an imperfection), geometrical (measurement of size and shape) and structural (whether there are any missing items or foreign objects). The main contributions of each study regarding innovative image-acquisition strategies are highlighted. The number of vision and lighting technologies currently available creates a significant diversification in the approaches followed by these studies. This is the reason why comparing studies across industrial fields and identify the most relevant contributions is very difficult to be done. Typically the system requirements are common to specific application field and for this reason transversal rules on how to design an efficient machine vision system cannot be established (Davies 2012b).

As mentioned in Chapter 1, studies describing machine vision systems applied to the tire inspection are not common. It would be beneficial to learn from previous studies suitable strategies to approach the development of an image-acquisition system for the detection of tire imperfections. Instead, an overview of the literature in other machine vision application fields was done to attempt to identify interesting concepts, best-practices and main difficulties. Strategies described in the literature to define an image acquisition system able to deal with circular objects with unpredictable and variable surface properties (brightness and roughness), may help in the definition of the visual system for the tire application.

In the inspection of circular objects the literature suggests that the design of the image-acquisition station should make use of the rotational symmetry to obtain measurements when the object is rotating (Davies 2012a). In order deal with variable surface properties, many studies have proposed the use of 3D laser scanners. The fact that the 2D technology is a function of the scene geometry, scene reflectance and illumination conditions, leads to situations in which a certain object appears completely different under different illuminations. Although laser scanners are also scene and position dependent and occlusion aspects are a problem, they seem to provide clear benefits over 2D cameras by being more stable across different acquisition conditions (Mian and Pears 2012). Nevertheless, the image acquisition station developed in the context of this research will mostly include 2D cameras to make images closer to what operators usually experience. For this reason special attention will be given to the lighting conditions. Illumination is extensively described in the literature as being an important aspect that influences the performance of the machine vision system, especially when the surface properties may vary among products. Some authors suggest that it is more profitable to spend time developing a quality illumination scheme that it is to develop complex algorithms capable of overcoming problems introduced by bad illumination. In agreement with its importance, the illumination scheme could be said to be performing part of the vision algorithm (Thomas et al. 1995). While camera selection can be done almost straightforwardly considering image requirements, designing a suitable illumination is still a rather “black art” (Davies 2012b).

Table 4.1 - List of industrial vision applications.

Inspection objective	Application field	Main contributions	Reference
Superficial	Textile industry	Backlighting illumination and 2D cameras are successfully used for fabric inspection.	Kumar (2008)
	Fruit quality inspection	The lighting system is simplified because the acquisition system rotates and translates the fruit to reconstruct its shape.	Blasco, Aleixos and Moltó (2003)
		A semi-transparent conveyor belt is used to allow illuminating from the bottom.	Blasco et al. (2009)
		The use of an infrared vision system demonstrated to be useful in the automatic assessment of olives.	Guzmán et al. (2013)
	Ceramic tiles inspection	Color sensors able to differentiate defects, color and flawless background.	Boukouvalas et al. (1998)
	Specular components inspection	Lighting system composed by light stripes.	Aluze et al. (2002)
		A line laser reflection from a moving surface is captured by a CCD camera.	Wedowski et al. (2012)
		Infrared thermography techniques successfully applied in detecting different surface and sub-surface anomalies.	Benmoussat et al. (2013)
Geometrical	Fruit size segregation	Use of multispectral imaging techniques.	Herrero-Langreo et al. (2011)
	Metal parts	3D imaging vision system successfully measures width and flatness.	Molleda et al. (2013)
Structural	PCB inspection	AN automated X-ray machine vision system was developed exclusively for the inspection multilayer misalignment.	Chuang et al. (2010)
		2.5D system that combines two line lasers to capture 3D depth and 2D texture information.	So et al. (2013)
	Tire industry	Laser line sensors to detect ply overlap, radial runout and profile measurement	Wordsworth (2008)

4.2 Proposed architecture for image acquisition system

4.2.1 *Mechanical system*

To acquire images of the tire surfaces' with adequate resolution and lighting conditions for the meticulous quality inspection task, single shot static captures does not seem feasible, considering a set-up of one camera per surface (inner sidewall, outer sidewall, tread, inner liner). Some preliminary tests were done in the sidewall but rapidly demonstrated lack of detail due to poor lighting effects, even with higher resolution sensors. Its curved shape, which constrains the fit of the entire tire surface into the camera's field of view, together with the resolution requirements, makes this strategy less viable. In fact, the outer square area of a typical sidewall for example, can range between 0.3-1m^2 while imperfections are at a completely different scale (minimum of 4 mm^2). In single shot acquisitions it would be extremely difficult to guarantee constant lighting conditions all over the surface. To correctly capture features as small as 4 mm^2, to guarantee uniform illumination and to distinguish lighting variations such as highlights and shadows at the scale of the imperfections, sequential acquisitions with successive snapshots demonstrated to be more adequate. Thus, the proposed acquisition scheme relies on a mechanical structure that rotates the tire while a set of cameras successively capture a small section of its surface. When a complete tire revolution is concluded, the whole area is covered. An alternative mechanical system would consist in having the tire fixed and rotating the vision equipment but an analysis done by another researcher, in the context of this project, revealed higher levels of complexity.

In order to guarantee stable image acquisition conditions, the mechanical system responsible for rotating the tire needs to fulfill several requirements. This mechanical system will serve as industrial prototype and for this reason, at this stage significant level of flexibility was desirable so that several configurations of the vision system and various tires could be tested. Hereby, the mechanical system described underneath, does not intend to be an industrial machine but rather a first materialization of a possible mechanical system.

The main considerations in designing the mechanical structure were formulated considering the tire deformation behavior and its intricate shape. The low stiffness and deformability intrinsic to tires makes them more vulnerable to deformations and small variations in shape which can result in vibrations while rotating noticeable in the images. In addition, its rounded shape makes the placement of the vision system more difficult, especially in the inner liner.

In sum, the requirements given to the mechanical system supplier were:

- Rotation stability guaranteed by mechanical supports and constraints;
- Automatic adjust to all tire dimensions;
- Constant and controllable rotational speed;
- Stable mechanical supports for optical and lighting systems;
- Image acquisition of all surfaces free from obstacles caused by mechanical components.

Figure 4.4 shows the final mechanical structure design. There are three crucial components that should be highlighted: walls with rolling spheres, rolling axes and moving wall. The tire is introduced in the machine in vertical position (Figure 4.4 (b)). For a better understanding, the two abovementioned walls were removed in this image. The yellow and red walls in Figure 4.4 (a) contain several insertions of rolling spheres. The two walls will slightly compress the sidewalls of the tire and restrain its rotation movement and minimize rolling slips when rotating. The spheres will provide sustainability to the rotation of the tire without creating significant friction. The motorized rolling axes transmit the rotational movement to the tire (Figure 4.4 (c)). The red wall moves horizontally along two linear axes and is positioned according to the dimensions of the tire being scanned.

In this industrial prototype the vision equipment for the inner liner acquisition is placed in the interior of the tire by means of an industrial robot (ABB IRB 120) as seen in Figure 4.4 (d).

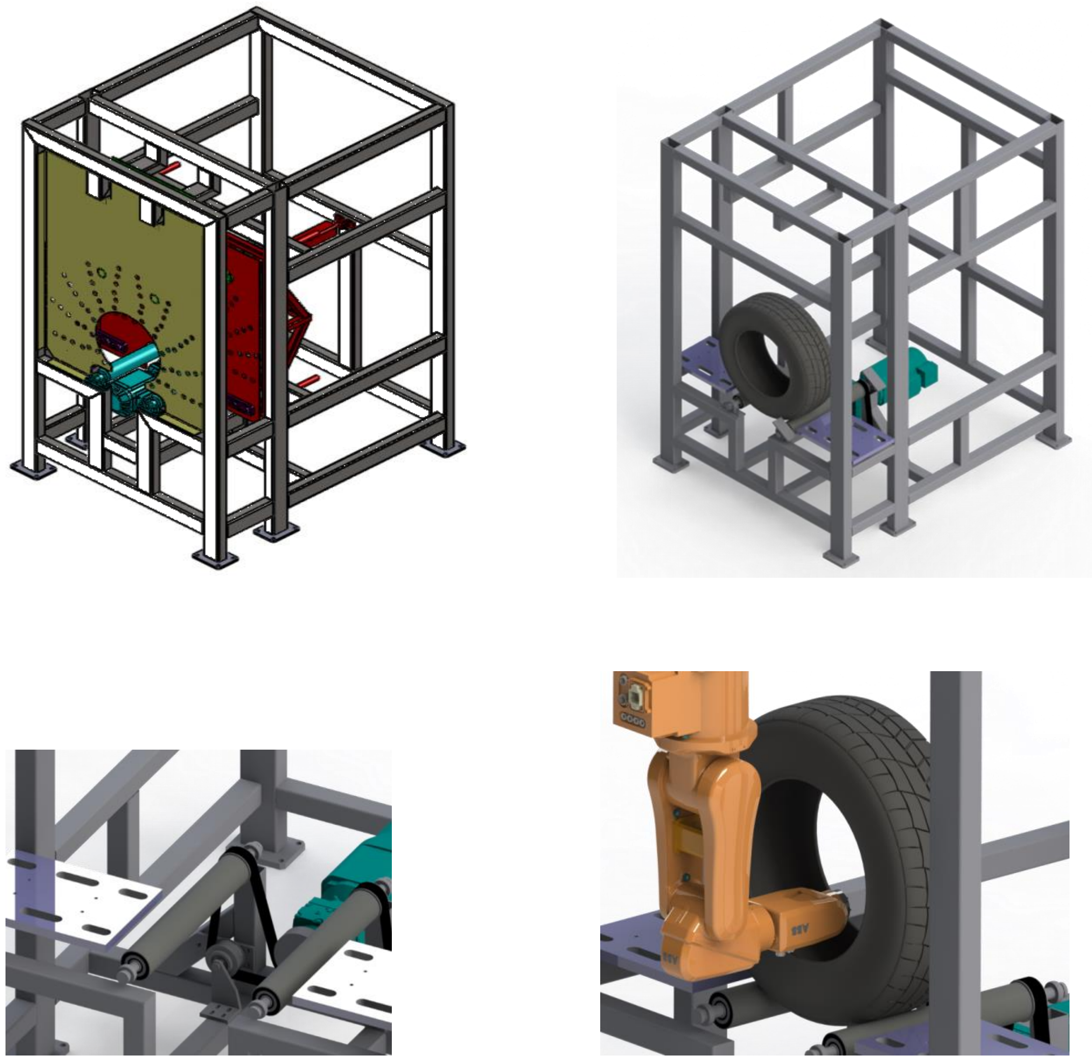


Figure 4.4 – Drawings of the mechanical system for image acquisition: (a) overall view; (b) tire placement; (c) detail of the rolling axes (d) robot in which the vision system for inner liner inspection is coupled.

The images in Figure 4.4 intend to enhance the comprehension of the reader by using simplified representations (minimal number of mechanical and electronic components and cabling). Even though, a photographic depiction of the actual prototype is shown in Figure 4.5.

Figure 4.5 – Prototype installed at the manufacturing plant

With this mechanical system, the steps to scan a tire follow the sequence illustrated in Figure 4.6. At this prototyping stage, some of these steps still require user intervention. The placement of the tire in the machine is an example of a current manual task that would greatly benefit from automation in subsequent stages of the project. This can be achieved by positioning a conveyor aligned with the machine entry.

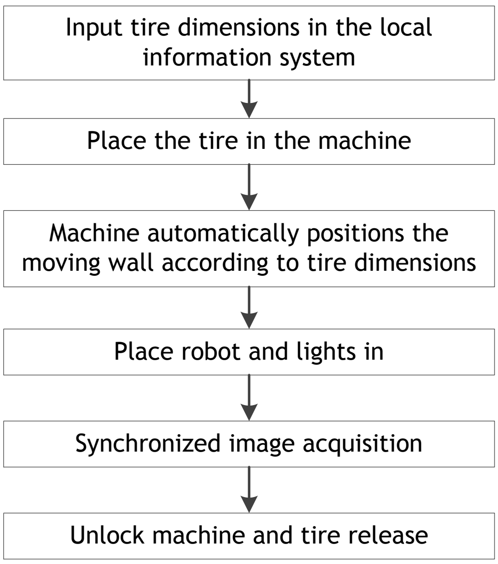


Figure 4.6 – Block diagram describing setup and acquisition

4.2.2 *Machine vision system*

Camera selection

Essential components of the machine vision system are cameras and light sources. In the context of this research, the selection of camera type and lighting was intended to be aligned with the strategy of acquiring images to serve both human-based and automatic inspection. Aiming at having the specialized operators performing the inspection process digitally is facilitated by attempting to recreate the usual appearance of the tire in the images, subsequently available through CAI. The current knowledge and expertise of the operators is maximized if the human visual perception of the tire is similarly mapped in the display where the operators will visualized the images. In case the relation between these two visual environments is prevalent, distinguishing between conforming and non-conforming items will resemble, until a certain extent, today's process (Yeh and Wickens 2001). Considering other vision technologies at this stage (e.g. 3D laser scanner) would require a significant learning process by the operators. The main advantage of mimicking appearance is that current human expertise would be applied and in situations where the machine vision system is unavailable, humans would still be able to continue performing the manual process as today. Furthermore, this strategy enables the continuous development of the automatic inspection system based on the participation of the visual inspectors in two activities: validating the appropriateness and quality of the images, especially in the accurate detection of imperfections, and in feeding the database with inspection decisions that can later be used for the development of automatic algorithms. Having this strategy in mind, most sensors in use in this machine vision system are 2D sensors that capture images in the visible spectrum of light similar to what humans perceive visually. Monochrome cameras were selected considering that there is insignificant color information in tires. Also these cameras often exhibit higher spatial resolution and sensitivity than their color counterparts. An analysis of the variety of imperfections that can occur in tires also sustains the choice of sensor technology. The fact that some imperfections do not have a depth component and are superficial or tonality variations suggest that 2D technology is adequate. Although, most imperfections present depth information, examples of imperfections without significant height variation (<0.5 mm) exist: dirt, and grease. The strategy followed is to use the lighting system to highlight the height of imperfections. Rather than using illumination with the only purpose that the camera captures the diffused reflected light, we aim at positioning the lighting system so that brighter or darker regions are created according to height/depth variations and result in outstanding regions from the surroundings (Hornberg 2006).

The proposed vision system operates by rotating the tire in front of a fixed camera while several acquisitions with few pixels wide will progressively occur. The complete surface should be acquired and this can be achieved if the rotation speed is defined according to the frame rate of the camera. Overlap in sequential images (when the rotation speed is too low) originates repetition of information and elongated letterings or embossments, while the opposite leads to uncaptured regions. For the sidewall acquisition, the adjustment between rotation speed and frame rate should be made considering the bottom part of the sidewall. The linear speed in the outer circle of the sidewall is higher than in the inner part and because a reconstruction of a rectangular planar projection of a circular surface is being made, some deformations will always occur (Figure 4.7 (b)). In this case, elongated effects, like the one seen in Figure 4.8, are preferable to compressed ones.

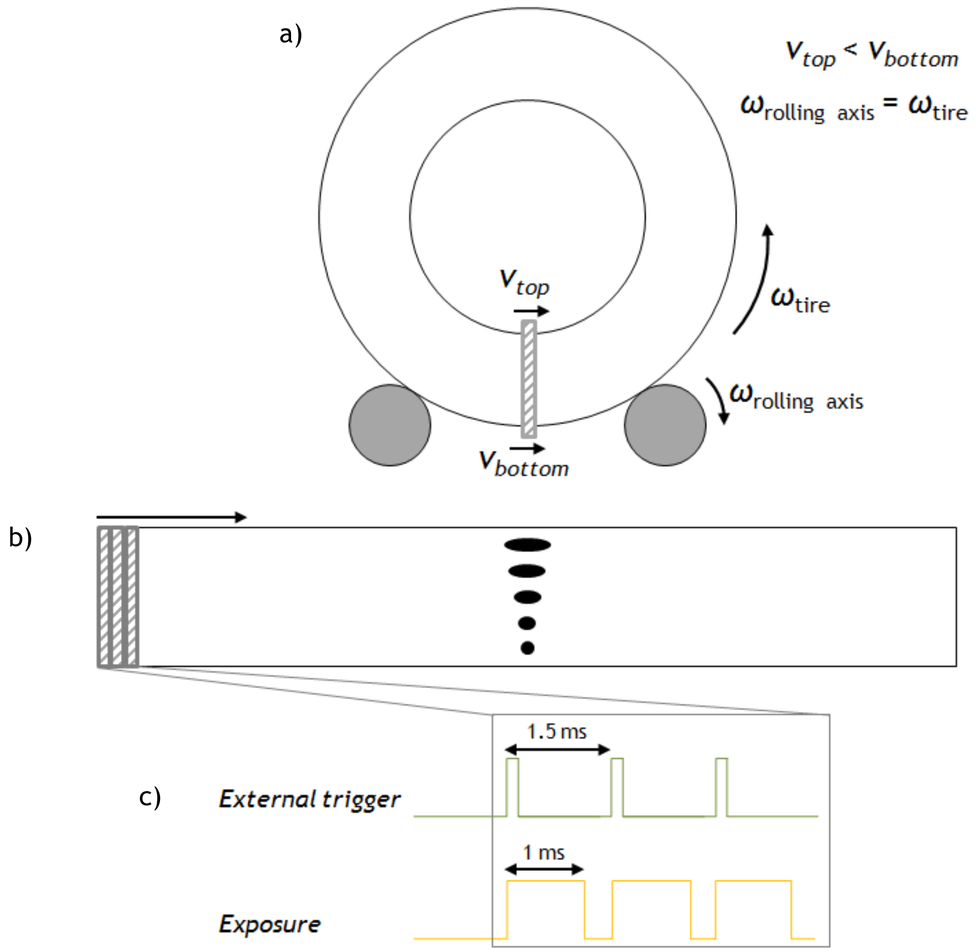


Figure 4.7 – Representation of the sidewall sequential image acquisition: a) the angular speed of the rolling axes is transmitted to the tire. The linear speed is not uniform along the sidewall height or the tire radius. b) The image is formed by concatenating successive frames. Repetition of information is unavoidable. c) The time diagram shows that each frame is captured at a regular defined external trigger rate.

Figure 4.8 - Elongation of the image close to tire inner diameter: (a) in yellow the real circle, (b) in red the elongated circle

Spatial resolution relates to the smallest feature that can be mapped in the sensor and is measured in mm/pixel. A suitable spatial resolution in this application allows operators and automatic algorithms to detect the smallest imperfection in the images. If the inspected object would be flat and uniformly illuminated, a single pixel defect might be considered an acceptable representation. However, the curved and non-homogeneous tire surfaces motivate higher spatial resolution. Assuming that 2 mm diameter is the smallest imperfection to be detected and 4 a reasonable number of pixels to map it in the sensor. The needed spatial resolution (R_s) is then given by:

$$\boldsymbol{R_s = \frac{S_f}{N_f}} \tag{4.1}$$

where S_f is the size of the smallest feature to be detected and N_f the number of pixels to map it. In this case, the needed spatial resolution is 0.5 mm/pixel.

Considering that the acquisition will follow a scan mode, the horizontal spatial resolution following the scan direction will be determined by scan rate and rotational speed. On the other hand, the vertical spatial resolution depends on the camera and lens specifications (sensor resolution and field of view, respectively) and this will mostly influence camera selection.

In the envisioned system, one camera will acquire images of the sidewall and a second one of the tread. To account for: all possible tire sizes, tolerance in tire position and safety margins, the field of view (*FOV*) needed in the sidewall is 300 mm (maximum sidewall height is 200 mm) and 350 mm for tread acquisition (maximum tire width is 275 mm). For being a particular case with specific requirements, the inner liner will have a significant different setup and will be discussed at a later stage of this chapter.

The needed camera vertical resolution (R_c) can be calculated as follows:

$$\boldsymbol{R_c = \frac{FOV}{R_s}} \tag{4.2}$$

By applying equation 4.2 it is possible to calculate that the minimum camera's width resolution is 700 pixels.

Having defined the camera type, acquisition mode and resolutions requirements, the selection of the specific camera and supplier was possible. The camera selected was Allied Vision Technologies GC 780 CCD camera with a maximum resolution of 782 (width) x 582 (height) and a 1/2'' sensor size. The operational mode (sequential acquisitions) would probably be also favorable for linear cameras instead of CCD matrix cameras but the desirable flexibility and willing to test different acquisitions modes motivated this selection.

With this camera the vertical resolution is 0.38 mm/pixel for the sidewall and 0.44 mm/pixel for the tread.

Figure 4.9 shows that this camera can also work likewise a linear camera. As the height of the acquisition window decreases, the frame rate increases, from 64 frames per second (fps) at maximum resolution (582 pixels) up to nearly 800 fps with a one pixel window or region of interest. Taking advantage of this technological capability and using shorter regions of interest seemed preferable. In this case the images will be formed by a sequential concatenation of frame-to-frame (Figure 4.7 (b)). In this application using few pixels window is advantageous to maintain uniform lighting conditions along the window height. Larger window area (achieved by increasing window height since width is fixed to 782 pixels) decreases the maximum frame rate but especially increases the lighting complexity. For successful inspections, especially human-based one, noticeable variations in lighting conditions along the image can disturb visual search and disguise imperfections.

The mechanical system rotates the tire at a constant linear velocity is 612.5 mm/s which for a standard 15’’ tire results in a complete rotation each 3.5 seconds. The acquisition window height will be set as small as possible and for this reason the acquisition will be done almost at the maximum frequency. The frame rate will be the same for both cameras (sidewall and tread). Considering a frame rate of 700 fps (avoiding operating at maximum frame rate is desirable to assure all frames are successfully transferred), the number of frames needed for the standard 15’’ tire is 2450 frames. To guarantee that the 2450 frames contain the complete tire revolution and some extra margin area, with the same spatial resolution as in the vertical direction, a window of 2 pixels height is needed. This 2 pixels window was acquired in the center of the sensor to minimize distortions. The cameras were triggered externally by hardware and each pulse will occur at every 1.5 milliseconds. The exposure time will be maximized although always below the trigger frequency. In this case exposure was set to 1 millisecond (Figure 4.7 (c)).

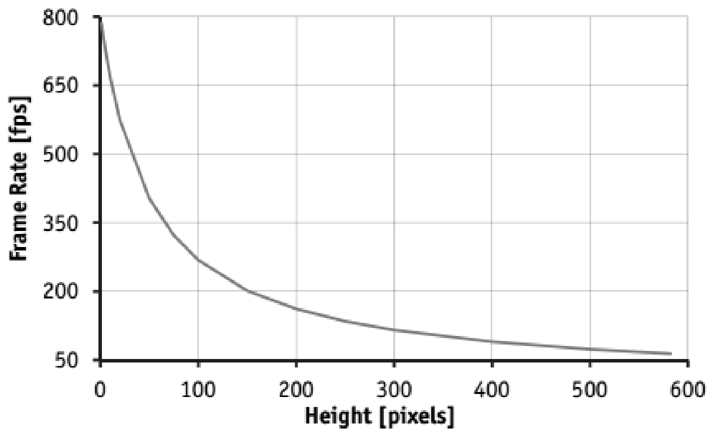


Figure 4.9 - Frame rate vs. height for Prosilica GC780

Lenses

Determining the suitable lenses was possible because the field of view and sensor size are known. Another important aspect for lens selection is defining the distance from the lens to the object (standoff distance). In this application large depth of field would be advantageous to maximize the tire area that is sharp in the image. This way the effect of the curvature of the sidewall, for example, is minimized because the decrease in sharpness is very gradual and the image is sharp along all sensor width or at least the unsharpness is imperceptible. Higher depth of field can be obtained by reducing lens aperture diameter or by increasing standoff distance. Reducing the lens aperture decreases the intensity of light reaching the sensor which, after a certain extent, might become impractical for the lighting setup. This is the reason why the strategy followed was to: increase the standoff distance, deploy a lighting system with high luminous power and reduce the aperture up to the limit in which the acquisitions still have adequate light intensity. The standoff distance from the sidewall and tread cameras to the tire is 600 mm.

The concept of optical magnification (*M*) needs to be clarified for the calculation of the desirable lens focal length. Magnification is the ratio between the image size of an object and its true size. Considering that in this camera setup, the *FOV* is mapped to the sensor width, the magnification is evaluated by:

$$\boldsymbol{M = -\frac{sensor\ width}{FOV}} \tag{4.3}$$

The GC780 camera contains 8.3 μm cells size and thus the sensor width is 6.5 mm. Because the image recorded by the sensor is usually inverted, magnification is a negative number. However, conventionally, magnification is assumed as positive. Therefore, magnification is 0.021 for sidewall and 0.019 for the tread. Having this said, the focal length (*f*) for a standoff distance (*d*) is calculated as:

$$\boldsymbol{f = d\frac{M}{1-M}} \tag{4.4}$$

The desirable focal length for tread is 11 mm and 13 mm for sidewall. Commonly available focal lengths for lenses in machine vision include 12 mm and 16 mm, which were the ones chosen for tread and sidewall, respectively. Slight adjustments in the standoff distance were made to compensate the focal length in use.

Lighting

As mentioned before a suitable lighting system is as important as choosing an appropriate optical system. Capturing a certain feature in an image is dependent on a successful trajectory of light from the illuminator, followed by reflection off the object, up to being collected in the lenses and later mapped in the sensor. All this reflectance process depends on the properties of the surface and the chosen illumination (Pernkopf and O'Leary 2003).

Initially, little or almost nothing about the optical properties of the tire surface were known. As mentioned in the literature, a real test object is always an unknown mixture of reflection, absorption and transmission (Hornberg 2006). Defining a lighting scheme to acquire images of tires is complex for many reasons. Its inherent dark color and low contrast, in addition to heterogeneous and curved surfaces result in many challenges in the lighting system design. Objects with sharp edges and smooth surfaces usually reflect light in a specular or mirror-like manner while rounded edges and rough surfaces result in light being mostly reflected in a diffuse range of scattered angles (Figure 4.10) (He et al. 1991). Anyway, these two cases are extreme and the effective reflecting behavior of common surfaces, likewise tire surfaces, is expected to be somewhere between (Wolff 1994; Rosati et al. 2009).

To further increase the complexity of the problem at hand, significant variations in surface properties among different tires occur. This variability was noticed in: color due to different materials or material mixtures in use, surface geometry due to product design, and direct reflections caused by the use of coating/painting surface treatments. These aspects can influence the vision system performance. In fact surface quality and roughness influence how the light is reflected, absorbed and transmitted, leading to only part of the light energy being reflected backward to the cameras lens.

A rapid test was done to analyze the impact of variable surface properties of tires in the acquired images. Two sample tires of the exact same article were acquired using the same lighting conditions. One was painted with oil coating and the second not. The two tires reflected light differently, and this was evident when the average gray values were compared. In some locations, the tire with surface coating retrieved an average intensity of 70 in a grayscale with 256 levels while the non-painted one got 55 (Figure 4.11).

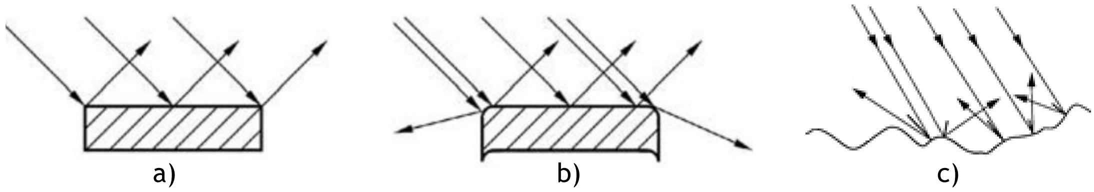


Figure 4.10 – Light reflection in sharp edge (a), rounded object (b) and rough surface (c) (adapted from Hornberg (2006)).

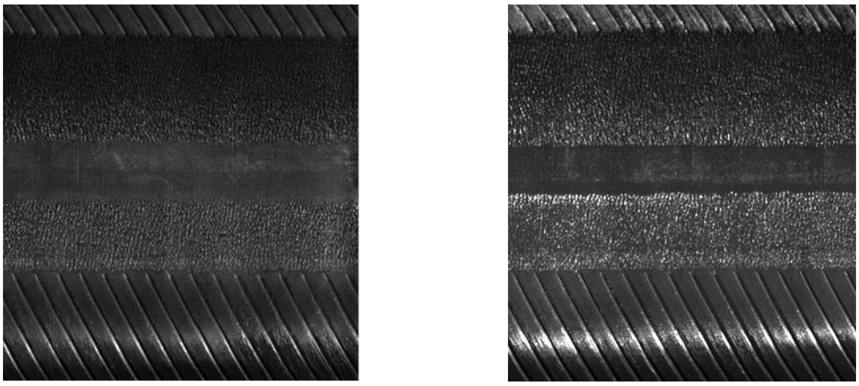


Figure 4.11 – Sections of inner liner images of the same tire article presenting: on the left a non-painted tire and on the right a painted tire.

In terms of lighting setup, several possibilities were analyzed. Dark field illumination and bright field illumination are two standard methods in surface quality inspection (Tian, Lu and Gledhill 2007). While in bright field the sensor captures most of the directly reflected light, in the dark field, the camera is located away from the specular direction of the scattered light (Figure 4.12). In dark field illumination the angle of incident of light with the surface's normal vector is very large. This results in uniform grey images being grabbed by the camera when acquiring flat surfaces. However, if there are some irregular regions (elevation or deepening) on the area illuminated, the incident light will be scattered in all directions. Then the image taken by the camera is bright or darker where the surface is irregular, which is the typical case of imperfections. Thus, in this application, this lighting setup can be advantageous to emphasize imperfections and make embossed or engraved letterings more viewable (Hornberg 2006). In practice, tire regions that are tilted away from the light will appear darker than regions that face the light directly. Even though, extremely shallow angles should be avoided because, as mentioned before there are some imperfections without significant three-dimensional component that could become undetectable. Oppositely, using bright field can originate problems such as saturation caused by direct specular reflections. This is the reason why, in this application, the lighting setup will include partial bright-field (transition between bright and dark field) mixed with dark-field illumination. In the literature there is not a clear dividing line/limiting angles between both (Hornberg 2006).

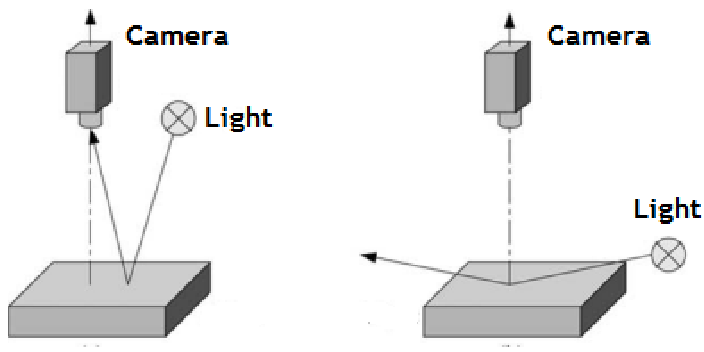


Figure 4.12 - Interaction between test object, light and camera: bright field setup on the left and dark field setup on the right (adapted from Pernkopf and O'Leary (2003)).

White light-emitting diode (LED) arrays were the light source selected for this application. Like in the camera selection, the light color was also selected in attempt to design an image acquisition setup resulting in images that are as close as possible to the operators experience when observing the tire under white light. Furthermore, selecting a different illumination wavelength could possibly highlight artifacts nowadays unperceived or reducing the intensity of some imperfections. Changing image features by using different light colors might be useful in a subsequent stage of the investigation if, for example, a specific imperfection needs to be further highlighted. For now, white LEDs consisting of a full range of wavelengths varying from 400-800 nm will be used. This wavelength interval is aligned with the spectral response of the sensor (400-1000 nm) and corresponds to the part of the spectrum to which the human eye is sensitive, which may be an important aspect to assure in the CAI.

The intensity of the lighting system needs to be extremely high in this application so that shorter exposure times can be considered and higher depth of field can be obtained by closing the diaphragm aperture without compromising an adequate average light intensity. In this case, LED arrays with luminous flux of 4000 lumen were selected (reference Bridgelux BXRA-N4000-00LE). Considering equation 4.5 that states that illuminance (E) at the test object decreases with the square of the distance (d), the LED arrays will be placed with short distances to the tire (few centimeters).

$$E = \frac{1}{d^2} \tag{4.5}$$

In most studies, the choice of the lighting system and its settings is done in an empirical way in which several experiments are done before an adequate lighting system and setup is identified (Geveaux et al. 1998; Coulot et al. 1997). Besides experimentations, some authors suggest mathematical models to foresee how light is reflected and optimized. In most cases, these models are applied to planar surfaces (Rosati et al. 2009). As an example, Coulot et al. (1997) proposed a method for planar surfaces which allows comparisons between several lighting. By applying a theoretical model of light scattering, the authors suggest the position of camera and light in comparison with object to obtain the best contrast between the object normal surface and defects. For non-planar curved objects, fewer publications exist. A study proposed by Tao (1996) in the area of fruit inspection suggested the use of spherical transforms to correct the non-uniform object reflectance over spherical shapes. In this study the complexity increases because each camera has to capture more than one object with different light gradients. Moreover, defects are supposed to be represented in the image in dark gray and lower intensities. Detections could be missed if these defects were located in darker regions due to curvature. One limitation of this study is that these mathematical transforms can only be applied to spheres and cylinders and not to more complex multiple-curvature surfaces.

Compensating for the curvature of objects in the physical setup was suggested by Valle, Gallina and Gasparetto (2003) and Rosati et al. (2009). Belonging to the same research group, these studies particularly evaluate the suitable lighting system for metallic automotive components with more than one curvature. A setup with a non-plane deformable mirror, which conveys the light rays onto every point of the surface to be inspected, was proposed at first, and later replaced by a series of flat highly reflective surfaces due to difficulties in manufacturing the mirror. Each surface of the object would be illuminated by a separate plane mirror, whose size and position were mathematically calculated according to the curvature radius of the surface. These methods were applied to shiny specular surfaces and the use of mirrors attempts to minimize saturations in the image.

Likewise Valle, Gallina and Gasparetto (2003) and Rosati et al. (2009) application to automotive curved components, also tires present a complex shape and multi-curved surfaces. Figure 4.13 shows an example of a possible lighting setup and camera positioning for the sidewall. The curved sidewall causes the normal to the surface to vary very rapidly, thus generating a discontinuity in the reflected light rays. This non-uniform light reflectance is even more noticeable when different tire sizes are tested. Having a fixed camera and lighting setup may not be adequate to acquire images of different tires with uniform and appropriate lighting conditions. Having this said, a system including adjustable light sources is proposed. Considering the example of the sidewall, two light sources will illuminate the complete sidewall height with some controllable overlap. The position and intensity of the light sources can be adjusted according to the tire under analysis. Larger tires will have higher distance between light sources, while smaller tires will have closer and lower intensity light (Figure 4.14).

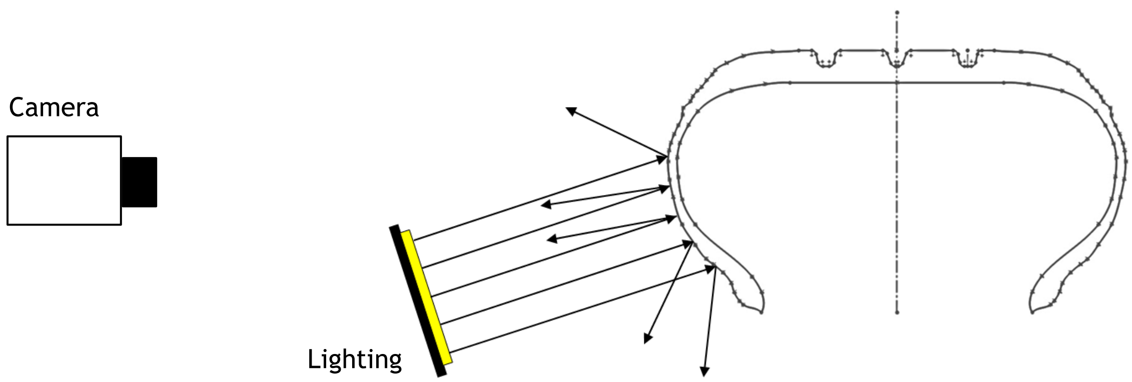


Figure 4.13 - Non-uniform reflectance of the tire curved sidewall

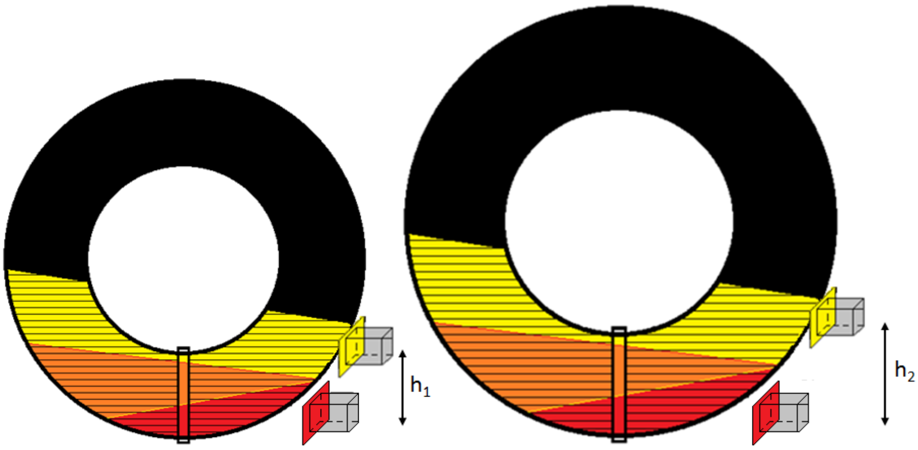


Figure 4.14 - Illustration demonstrating the two light sources and the need for its reposition. The smaller tire on the left requires a height (h_1) while the bigger tire on the right requires h_2 between the two light sources to assure the illumination of the entire sidewall.

Implementing a lighting system, in which the light source position can be adjusted, was made possible through the attachment of the LED arrays to articulated arms (Figure 4.15). These articulated arms are driven by servo motors and assembled according to the needed degrees of freedom. All lighting position adjustments were then configured by changing the rotation angle of the servo motors. The servo motors used in this application were Dynamixel AX-12+.

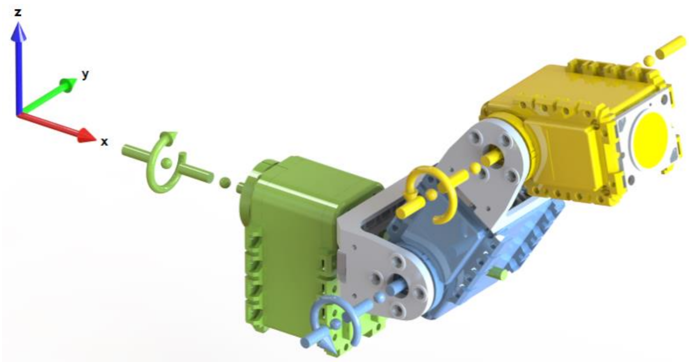


Figure 4.15 - Example of an articulated arm for lighting support.

Depending on the tire surface under analysis (sidewall, tread or inner liner) the articulated arm was assembled with a different number of servo motors because the needed lighting flexible adjustments vary. Table 4.2 discriminates the configuration of the articulated arm according to the tire area. Sidewall is the area that requires a more complex lighting fixation solution. As illustrated in Figure 4.14, the significant sidewall height variation among different tires (minimum 82 mm and maximum 200 mm) requires that the point of incidence of light is adjusted. Besides specifying the desirable incidence position, the articulated arm should also allow adjustments in the orientation which in this case results in controlling the angle of incidence of light. This is the reason why the articulated arm setup for the sidewall presents two parallel joint axes that allows rotation in the y direction (these servos are in yellow and blue in Figure 4.15). In addition there is a third servo that controls the rotation of the articulated arm around x (servo in green in Figure 4.15). Assuming the definition of degrees of freedom as the number of joint angles that can be independently controlled, three degrees of freedom are needed for the sidewall lighting system. By specifying a desirable angle and point of incidence in the reachable workspace, and knowing the inverse kinematics of the system, the angle for each joint can be calculated. Solving the inverse kinematics of the system was also performed.

Table 4.2 – Configurations of the articulated arm according to the tire area

Tire area	Degrees of freedom	Possible adjustments
Sidewall	3	Angle and point of incidence
Tread	2	Angle of incidence
Inner liner	1	Point of incidence

Another aspect in the lighting system that can be controlled is the LED intensity, done by means of adjusting the PWM (pulse-width modulation) duty-cycle. The articulated arms can be repositioned according to the curvature of the tire to approximately guarantee a constant distance from the object. Nevertheless this has revealed to be hard to attain due to the mechanical constrains of the joints and significant object curvature variation. For this reason, controlling the light intensity can also be important. Closer objects can be illuminated with less light intensity than farther objects.

A detailed description of the image acquisition setup for each tire area will be done. Starting with the sidewall, which was already used as an example along this chapter, the proposed setup is illustrated in Figure 4.16. The home position of the two articulated arms is vertically aligned and 150 mm apart. The articulated arms and camera that will position the lighting for the outer sidewall acquisition will be fixed on the machine structure while the articulated arms and camera for the inner sidewall acquisition will be fixed to the moving wall. Both will acquire images simultaneously. The center of the cameras (in red on the right part of Figure 4.16) are located in vertical radial plane of the tire and vertically positioned so that the FOV can capture all sidewall heights. The physical prototype is shown in Figure 4.17.

Having the possibility to adjust the lighting conditions (intensity, angle of incidence and point of incidence) according to the tire under analysis seems to be essential to guarantee adequate image quality across tire sizes. To configure each variable according to a certain tire, the user operating the image acquisition station should create a recipe in the system database. This recipe will store all lighting variables described before so that tires belonging to the same article are acquired with the same conditions. The significant flexibility available to adjust lighting conditions requires that some guidelines are stated. This way, independently of who is operating the system, there is consistency in the criteria to define what an adequate lighting setup is. To better define and visualize the effect of different lighting conditions, the user is provided a visualization window in which the whole sensor matrix is shown and the 2 pixels window is highlighted (Figure 4.18). Several image attributes are available so that the user can get some quantitative feedback over lighting adjustments. Table 4.3 lists the information available and what the adjustments should aim at for each of them. Special attention should be given to the intensity profile that shows the average intensity of the two pixels along the image width and how balanced the light across the tire is. The effect of turning off or on a LED array in the intensity profile can be seen in Figure 4.18.

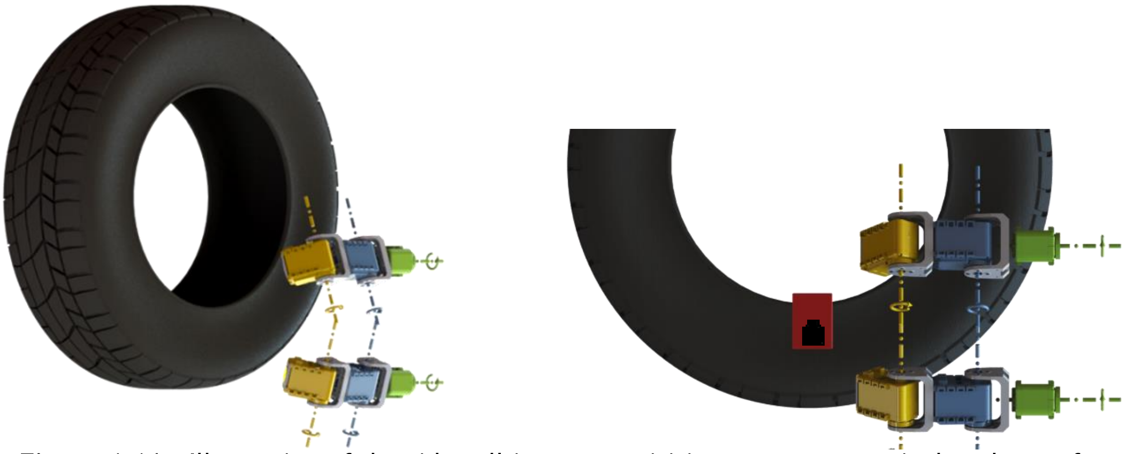


Figure 4.16 - Illustration of the sidewall image acquisition setup: two articulated arms for light positioning and one camera (in red).

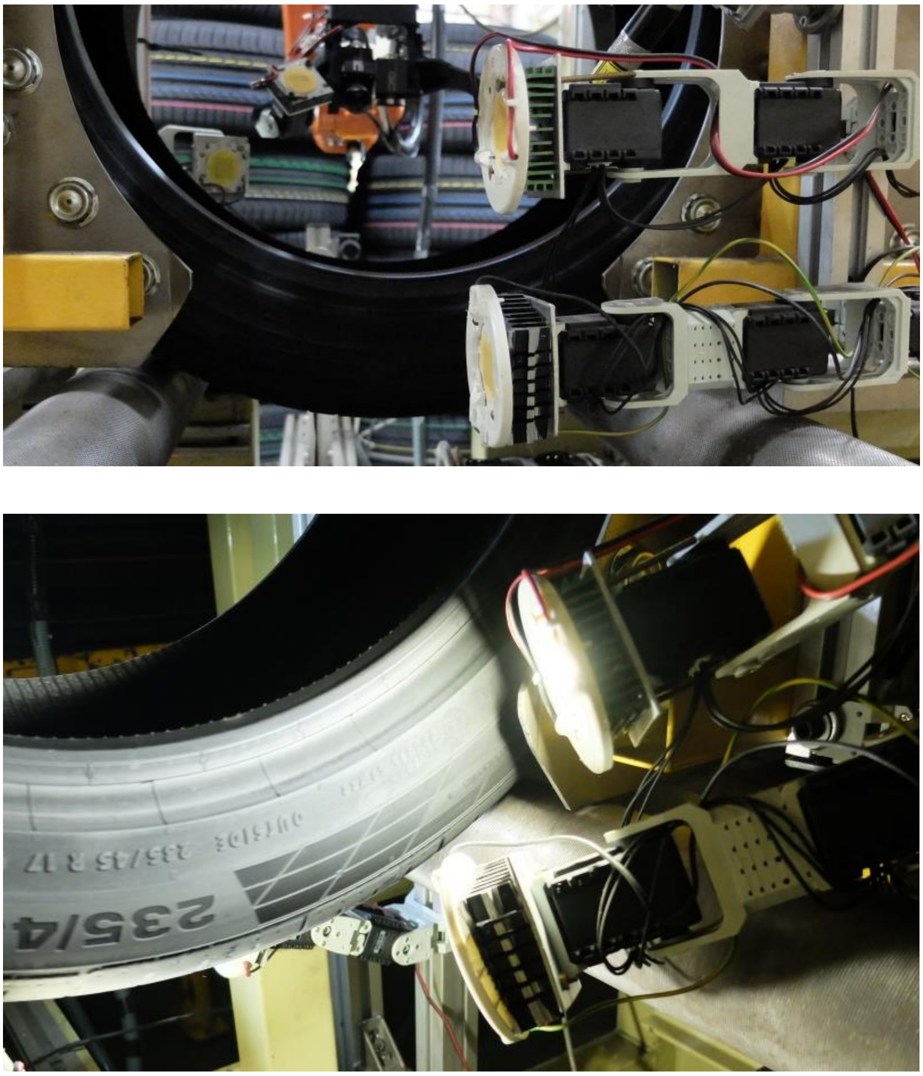


Figure 4.17 - Pictures of the prototype: in the top image the articulated arms are in the home position, while in the bottom image an acquisition is taking place.

Adjust lighting positioning to obtain uniform lighting conditions that minimize the effect of tire curvature, differences in tire dimensions, color variation, but that on the other hand highlights imperfections, is the overall objective. The lighting configuration is typically done using a conforming tire to avoid imperfection-specific illuminations that may not be optimal in other cases (Figure 4.19). The default configuration is done following the criteria described in Table 4.3 and attempting to create a dark field illumination aiming at highlighting most imperfections.

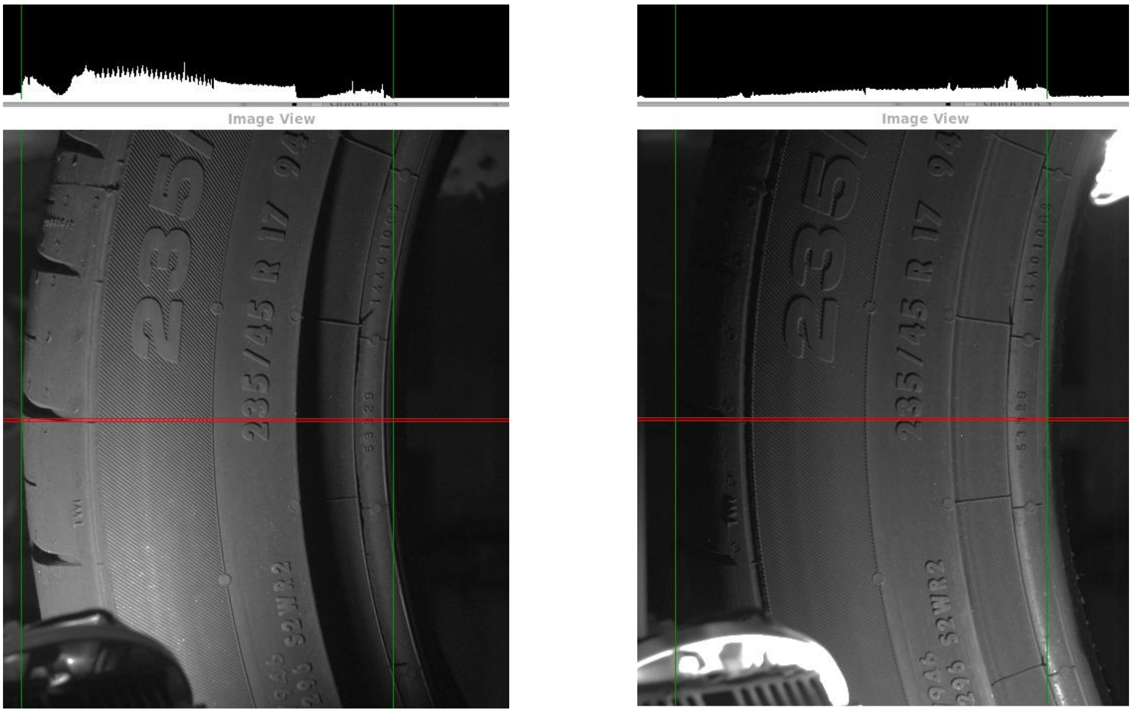


Figure 4.18 - Example of user interface environment when defining a lighting configuration. The window being captured is shown in red. On top of each image the intensity profile is plotted. In the left image only the bottom LED array is emitting light and on the right, only the top LED array is on.

Table 4.3 – Image attributes computed to define a lighting configuration

Image attribute	Criteria
plot intensity profile	Visualize the spatial location of darker and brighter regions and adjust variables to attain more uniform light conditions
mean	Similar mean should be found in all surfaces of a given tire
median	Similar median should be found in all surfaces of a given tire
standard deviation	Adjust variables to minimize standard deviation to attain more uniform light condition across the tire
max	Avoid 255 intensity values that represent saturated pixels
min	Avoid low intensity values that can lead to obscure imperfections

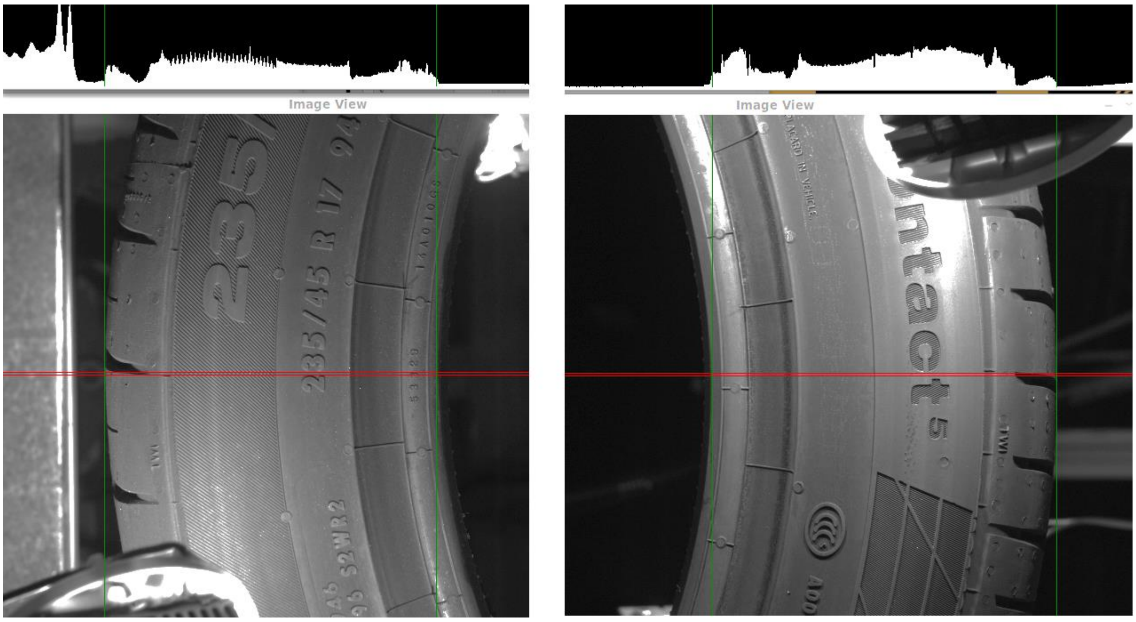


Figure 4.19 - Lighting configuration for a conforming tire. On left the inside sidewall and on the right the outside sidewall of the same tire are shown.

The tread is the most planar surface of the tire and for this reason the lighting positioning system presents fewer degrees of freedom comparing to the one defined for the sidewall. Because the camera is positioned in the vertical radial plane, the surface being acquired is approximately parallel to the camera sensor. This is always the optimal location to acquire sequential images of the tread and for this reason there is no need to move the lighting system to adjust the point of incidence. Only the angle of incidence should vary to accommodate for different reflectance that occurs for various tread patterns and color variations. The angle of incidence can be adjusted like in the sidewall case, by changing the joint angles of two parallel servo motors (Figure 4.20). One articulated arm is fixed in the mechanical outer structure, while the other is rigidly attached to the moving wall and therefore always positioned at the same distance from the border of the tire tread. Similar to the sidewall there is also some light overlap at the center of the tread which can be adjusted by means of the articulated arms repositioning and control of light intensity.

Figure 4.21 shows the joint setup for the sidewall and tread image acquisition. The acquisition location is optimal in both cases because of the avoidance of camera tilting and correction algorithms to compensate for distortions. Nevertheless the physical concentration of several light sources may cause some interference among them because the two acquisitions will occur simultaneously. Avoiding, for example, that the light sources of the sidewall are directly visible at the tread camera is of major importance. Some physical barriers were placed to minimize this interference and avoid glare effects.

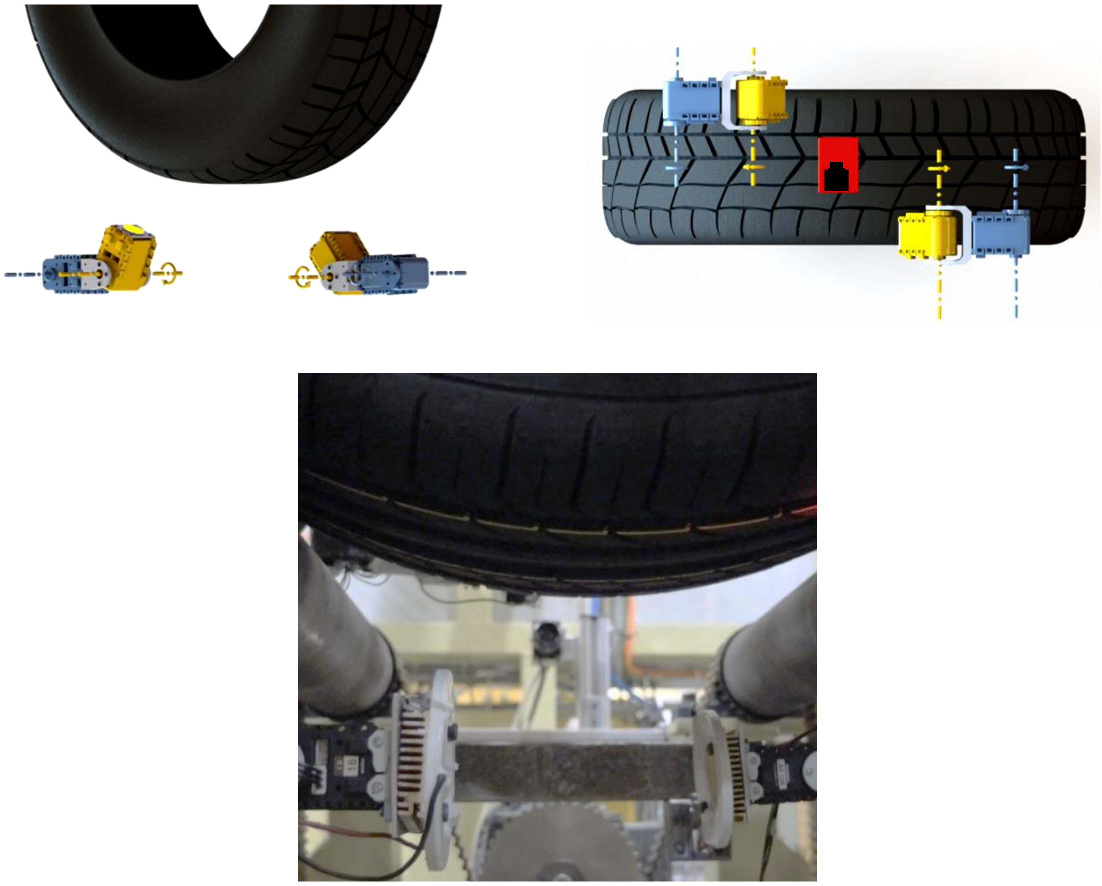


Figure 4.20 - Illustrations and picture of the tread image acquisition setup. The lighting system can be seen in the top images colored in yellow and blue while the camera is illustrated in red on the right. The bottom image aims to better show the prototype context.

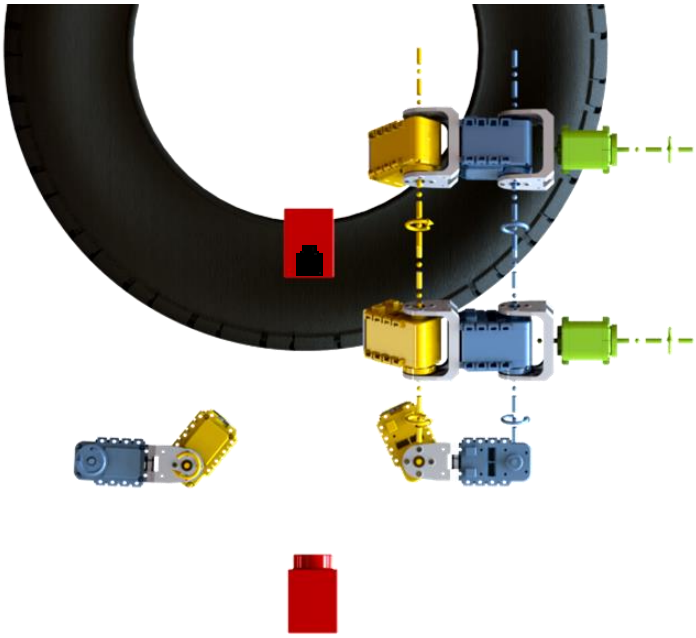


Figure 4.21 - Schematic representation of the vision system for the tread and sidewall acquisition.

The inner liner acquisition system is the only setup that requires vision sensors to be re-positioned and not remain fixed like previously described for the sidewall and tread acquisitions. The vision system is composed by two cameras GC 780, each of them acquiring approximately half inner liner with some FOV overlap (Figure 4.22 and Figure 4.23). Each camera FOV is illuminated by one LED array, mounted on a servo motor. All these equipment needs to be placed equidistantly to both walls of the tire, otherwise one camera and lighting will be closer to the object surface that the other, which could compromise the objective of having uniform lighting conditions. An industrial robot ABB IRB 120 is used to centrally position the vision equipment. For the purpose of the investigation, it was assumed that this setup could be validated by acquiring only half inner liner with one camera. A fish-eye lens with 2 mm focal length and 180º FOV was used. The fact that the clearance between the tire surface and lens is very small (in some cases less that 100 mm in comparison to the 600 mm standoff distance in tread and sidewall) suggests the use of a fish-eye lens to provide a full view of the object. The drawback consequence of providing a large FOV (~180º) is that fish-eye lenses introduce significant distortion. The fact that only a two pixels window is being acquired minimizes this effect.

Two cameras in the inner liner need to acquire approximately the same area that in the outside surface is being acquired by three cameras (two sidewalls and one tread). Nevertheless the same camera is being used which results in images with lower resolution. Even though, the lowering of resolution does not seem significant because it still retrieves an acceptable value of 0.58 mm/pixel.

Lighting adjustment is essential in the inner liner. Desirably articulated arms with two servo motors would be used to control angle of incidence. But due to space constrains only one servo is used for each LED array. Changing the point of incidence and LED intensity enabled acceptable acquisitions conditions across tire dimensions.

Figure 4.22 - Schematic representation of the vision system for the inner liner acquisition.

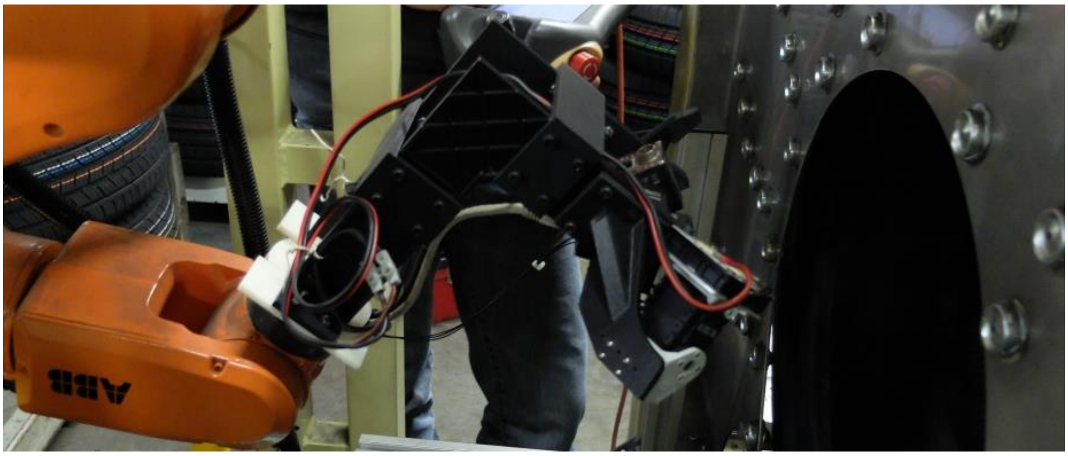


Figure 4.23 - Illustrations and picture of the inner liner image acquisition setup.

Defining adequate lighting conditions for tire image acquisition is a rather complex task. After performing the acquisition of a sample of over 1000 tires, it became evident that most difficulties were found in the inner liner and sidewall image acquisitions. The inner liner acquisition difficulties were mostly related with space constraints that limits the lighting position adjustments. This, together with the highly curved area, inevitably originates non-uniform light conditions even upon adjusting light intensity. Also specular spike effects in tires with oiled coatings are harder to minimize.

The main challenges presented by the sidewall come from ensuring adequate lighting effects across variable letterings and imperfections. For being an area visually accessible to costumers and that suffers low wear, most information is embossed in this surface. This information leads to the presence of small geometric features, greatly prone to defects. Also, because costumers will observe this area more often, finishing standards are rather high.

Having dark field illumination is expected to highlight imperfections. In fact the normal to the area where the defect is located is expected to change very rapidly creating locally brighter or darker areas. Figure 4.24, Figure 4.25 and Figure 4.26 show an examples of the appearance of imperfections and its local light variation effect in sidewall, tread and inner liner, respectively.

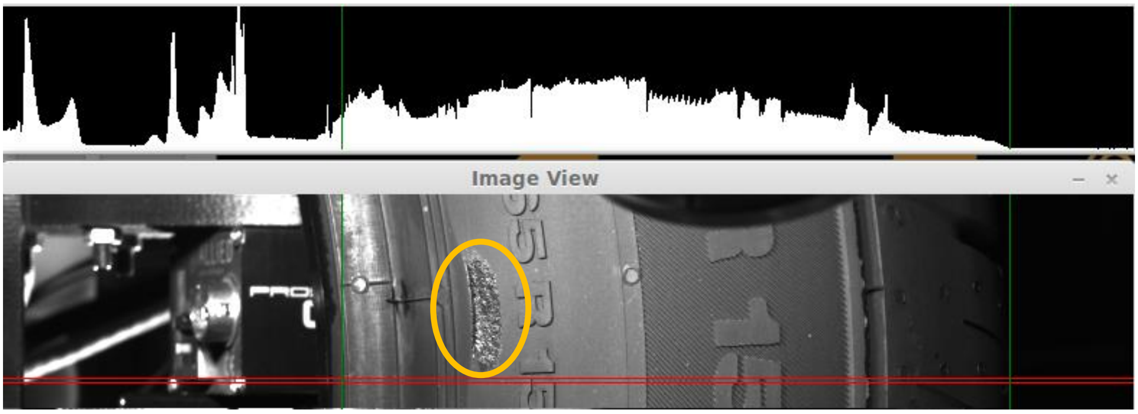


Figure 4.24 - Example of a sidewall imperfection, manually delimited with an orange elliptic shape. Brighter intensities are visible in the imperfection region.

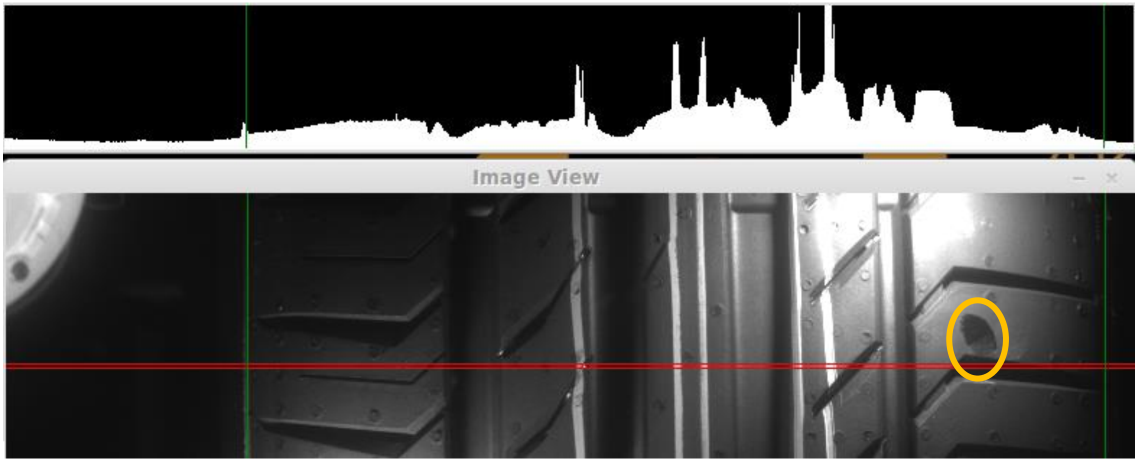


Figure 4.25 - Example of a tread imperfection, manually delimited with an orange elliptic shape. Darker intensities are visible in the imperfection region.

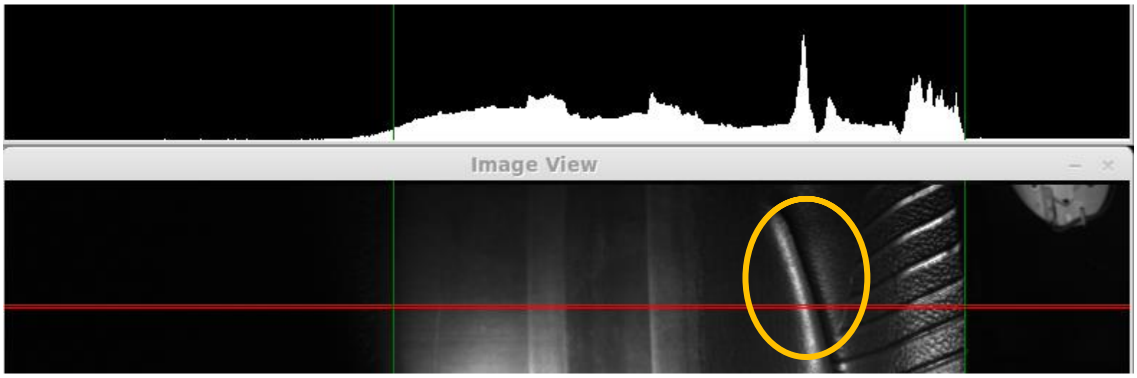


Figure 4.26 - Example of an inner liner imperfection, manually delimited with an orange elliptic shape. Variations from brighter to darker intensities are visible in the imperfection region.

The methodology defined to validate the quality of the images obtained is to show them to inspectors and ask them to perform inspection based on them. This will be the matter described in the next section. The main objective is to provide operators with images without: ambiguous features, insufficient illumination or excessive glare. This can only be achieved if a close interaction with operators is maintained. By incorporating their feedback, the aim is to understand the luminance values and lighting features that result in an improved quality detection performance. Having the operators performing an intermediate validation step of the quality of the images and storing their decisions based on those in a database, is believed to considerably benefit the latter development of automatic algorithms.

Instead of trying to identify the most suitable lighting conditions beforehand by means of mathematical models of light, the strategy is to try to incorporate the results of the performance of operators at CAI to improve and adequate the lighting conditions.

Later on in this research some changes in the lighting system may also be motivated by the performance of the detection algorithms. In fact, while operators may develop mechanisms to distinguish between artifacts created by inappropriate lighting and imperfections creating abnormal lighting effects, algorithms may have more difficulties in doing so. Nevertheless for both purposes, the clearer the images are, more likely a successful inspection is.

4.3 Validation of image acquisition system

This section aims at obtaining answers to the first sub-research question posed in Chapter 1 and recalled here in Figure 4.27. As mentioned in the previous section, a feedback loop is proposed to support the validation and the continuous improvement of acquisition conditions upon operators' detection performance. The experienced and specialized operators are a fundamental element in validating the image acquisition. In an iterative manner, acquisition conditions that were at first defined in a structured but still experimental basis (following the criteria defined in Table 4.3) can be improved. Along this research various experiments were done in collaboration with operators. The one hereby described is restricted to the evaluation of the appropriateness of the images as a vehicle of information about the tire. If this step is successful, eventually the operators will have a similar performance in assessing the tire physically or digitally and also implementation of algorithms for imperfection detection can be considered. Thus, for now, the aim of this experiment is restricted to the validation of the image acquisition station (in green in Figure 4.2). The detection rate among operators and the comparison with today's process will be matter of subject of the next chapter.

During this research, the validation of the feedback loop process was implemented and tested over a 3 month period at Continental Mabor facilities. Six inspectors with various profiles (age, experience, average performance) were selected to participate in this field experiment. CAI tool was made available in a room aside from the production line. The setup was equipped with a standard desk, a monitor which was placed in front of the participant and mouse for the user to be able to interact with the application (Figure 4.28). Only one operator at a time was requested to participate in the study to avoid any line stoppage, thus jeopardizing the plant production goals. Further details on the design of experiment (sample and subject selection) will be given in the next Chapter.

Research question: How should the image-acquisition station be designed to assure acquisition of unambiguous images of the object?

↓

Methods: Experimental testing and iterative validation procedure

Figure 4.27 – Research question and respective methods used for its test.

Figure 4.28 – Photographic depiction of the workplace proposed for CAI.

Training the inspectors on how to use CAI tool is mandatory and should take place prior to the start of the experiments and repeated periodically. Instructions on how to use the tool were presented verbally and some exemplifying cases were given in the CAI tool. Along two weeks the operators could come at any suitable time and practice by themselves CAI environment with some random images. A minimum of two practice sessions was advised. A researcher would be available to assist operators with any aspect.

The validation of the machine vision system's capacity of acquiring adequate images of tires was defined to be mostly based on the successful acquisition of non-conforming tires. At this stage of the research, it was more critical to evaluate if all imperfections were being correctly captured in the images than evaluating is the conforming tires were adequately represented. Rejecting more OK tires (false positive) will be a natural effect of changing the inspection environment and should be possible to recover upon inspectors' gain of confidence in the automatic acquisition system. However at this stage, missing a nonconforming tire can indicate that the imperfection was not clearly featured in the image. In order to conclude about the effectiveness of imperfection acquisition, the operators in this experiment were given only NOK images. A sample of 300 NOK tires was acquired in the image acquisition station, distributed among the maximum variety of NC codes and following its general frequency. Cases with variable level of imperfection intensity were considered. In the majority of the cases, each NOK tire was acquired according to lighting setup previously defined for an equivalent OK tire. When acquiring the NOK tire, the imperfection location was registered in the system database.

The acquisition of 300 NOK tires originates roughly 300 NOK images because normally each NC is only (or mostly) visible in a single tire surface (sidewall, tread and inner liner). The 300 images were subdivided in smaller sessions that were made available for the operators on daily base. A list of imperfection codes of each image was given to the operators. The operators' task consisted in localizing the imperfection and surrounding it with a rectangle (Figure 4.29). The coordinates of the rectangle drawn by the operator were then compared to the coordinates of the rectangle registered at the image acquisition station.

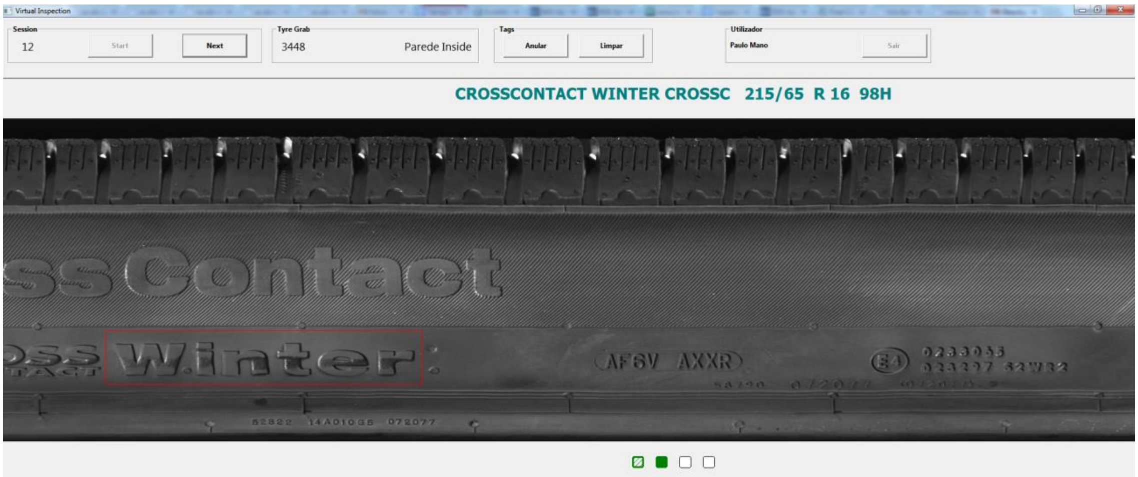


Figure 4.29 - CAI user interface and imperfection mark.

The objective of this experiment is to essentially orient the visual search of the operator by providing the hint about the imperfection that each image contains. With this approach it was intended to restrict the number of human factors influencing the validation of the image acquisition station. Furthermore, the fact that the operators were asked to do a guided-inspection (knowing beforehand that the image was NOK and its code) might positively contribute for their training and experience in interpreting image features.

Figure 4.30 shows the feedback loop used in this experiment. The steps done at the Image Acquisition Station include: the configuration of a recipe with the lighting conditions for each tire, acquisition of the images of the NOK tire and registration of the NC coordinates in the corresponding image (typically the imperfection is only visible in one tire area). The image containing the imperfection is shown to 6 operators. If the imperfection location assigned at least by one of the operators matches the one previously registered in the database by the image acquisition station user (within a certain tolerance), the imperfection acquisition is assumed as valid. If this happens, the lighting setup for this tire reference is deemed valid. In case none of the operators signs the imperfection correctly, the tire, if available, is resent to the image acquisition station for acquisition reconfiguration. Due to shop floor space restrictions, there isn't always the possibility of keeping the tires on hold while CAI is taking place. Moreover, situations in which the tire is physically available but during the period on hold has been exposed to conditions that make it unsuitable for image acquisition (dirt, dust, etc.) also occurred. When this happened, new tires with the same imperfection code were collected and tested.

The feedback loop illustrated in Figure 4.30 was the methodology followed along this research. A suggestion to continue to perform this development loop was made to Continental. Enlarging the number of tested cases to attempt to acquire a suitable sample of each NC code, and the improvement of the reliability level of the acquisition station might continue to occur, step by step in an iterative mode.

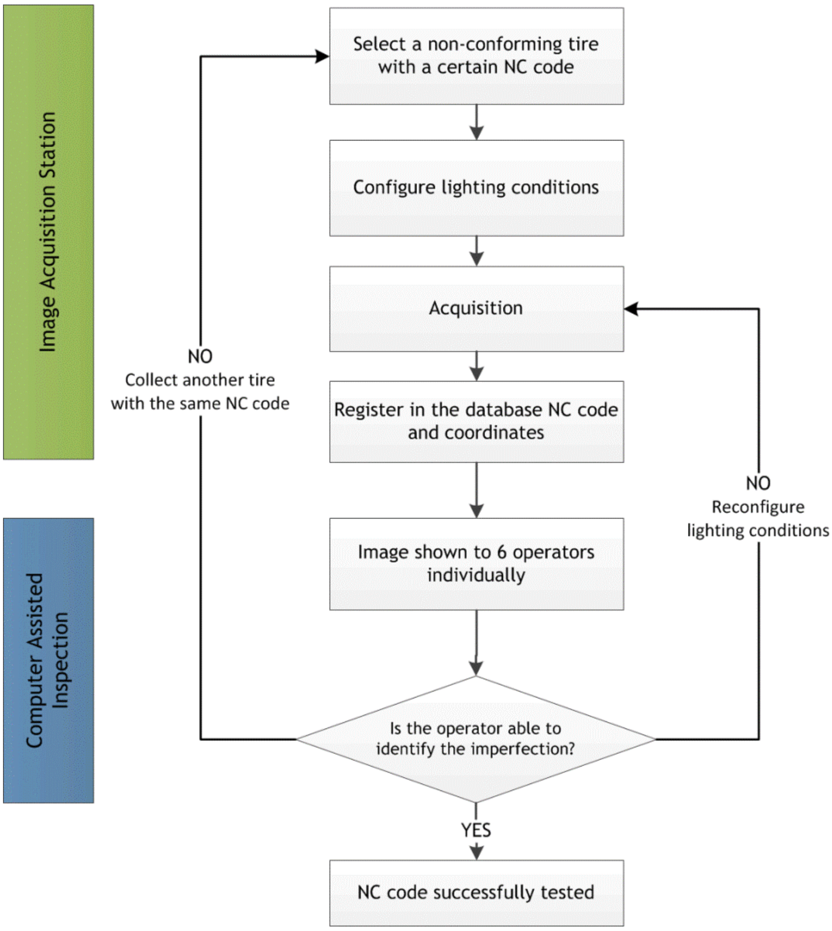


Figure 4.30 - Validation process defined to continuously improve tire images.

The results of the experiment were subdivided by tire area and are shown for the sidewall, tread and inner liner in Figure 4.31, Figure 4.32 and Figure 4.33, respectively. The 300 NOK images selected for this experiment are distributed along 41 NC codes. Although it may seem a number distant from the total number of NC codes (76), these 41 codes actually represent 92.6% of the total frequency of NCs in a 6-month period. The remaining codes were not tested for not having occurred in the 3-month period of the experiment.

The percentage of successful imperfection detection cases is predominant in the results obtained. Besides analyzing the matching results, close interactions were kept with the operators to incorporate some of their qualitative feedback. Corrections in the average intensity value, light intensity increases in some particular regions and improvements in CAI user interface were made along this process.

Following the real trend of more imperfections' occurrence in the sidewall, 175 tests were done in the sidewall. Two unsuccessful cases occurred (1.1%). One case was not possible to be re-configured for tire unavailability. In the second case the lighting adjustments did not retrieved a better outcome (imperfection located at the bead edge). Three additional cases were missed at first trial but successfully evaluated after lighting adjustments were done (cases were also located at the bead edge). These replaced the previous failure cases and appear as successful ones in Figure 4.31. Both quantitative (analysis of matches) and qualitative (informal interactions with operators) results suggest that operators have some difficulties in detecting imperfections located at the bead edge (Figure 4.34). Depending on the tire shape, the bead edge can be almost perpendicular to the camera sensor which makes its acquisition barely impossible with the sidewall camera. Other imperfections that occur in the bead (example of NC code 42 in Figure 4.31) are successfully acquired for being located in the part of the bead that remains approximately parallel to the camera sensor. Although the number of failures is not significant, some strategies to minimize this issue should be defined in the future. The results for the tread and inner liner also retrieved positive outcomes. 97.1% and 94.5% of the images were successfully evaluated for tread and inner liner, respectively. As mentioned before, the lighting conditions for the inner liner are sometimes difficult to be adequately defined with the current setup and this aspect is reflected in the slightly poorer results in this area. More tests in the inner liner should be done to conclude about the need of considering alternative lighting or cameras.

The change of environment from a physical manual inspection to CAI seems not to have significantly affected the capabilities of the operators in identifying imperfect regions in tires. The fact that the imperfections were appropriately captured together with the strategy defined to acquire images with an appearance as close as possible to the real object, contributed to this fact. Even though, for the most ambiguous cases, a continuous training plan should be defined so that operators can improve their ability to distinguish reflectance changes caused by imperfections from other artifacts. The operators evaluated very positively CAI as a tool for the detection of imperfections. Some examples of their qualitative feedbacks include:

- “images with good quality; tire appearance very close to reality”
- “it is much easier to observe the tire, especially for the tread and inner liner”
- “some imperfections became more evident and detailed”

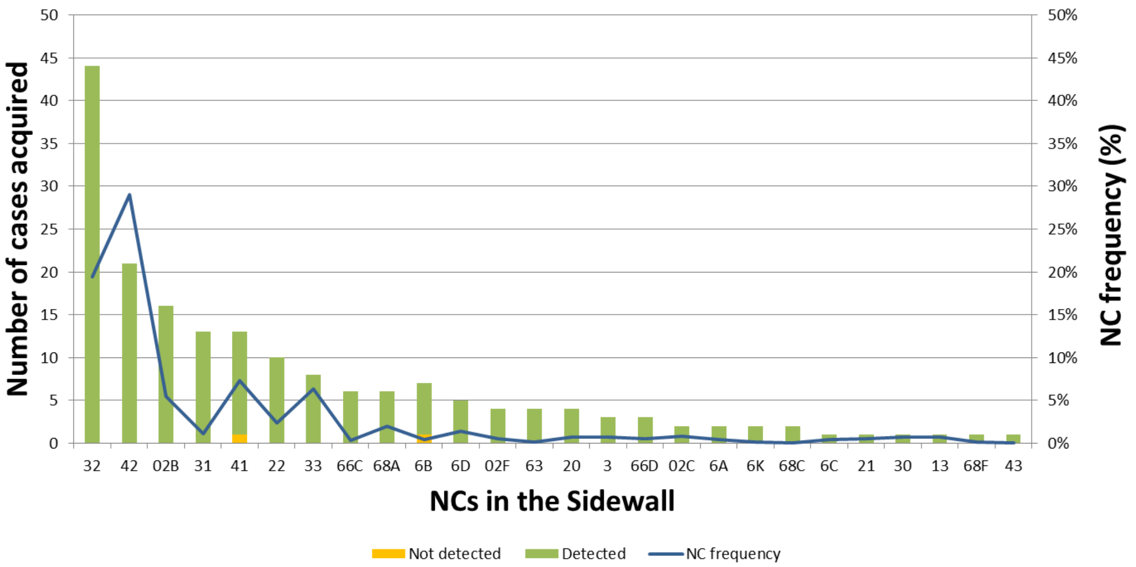


Figure 4.31 - For each NC in the sidewall the plot shows: the number of successful and unsuccessful validation cases and its frequency of occurrence in the past 6 months.

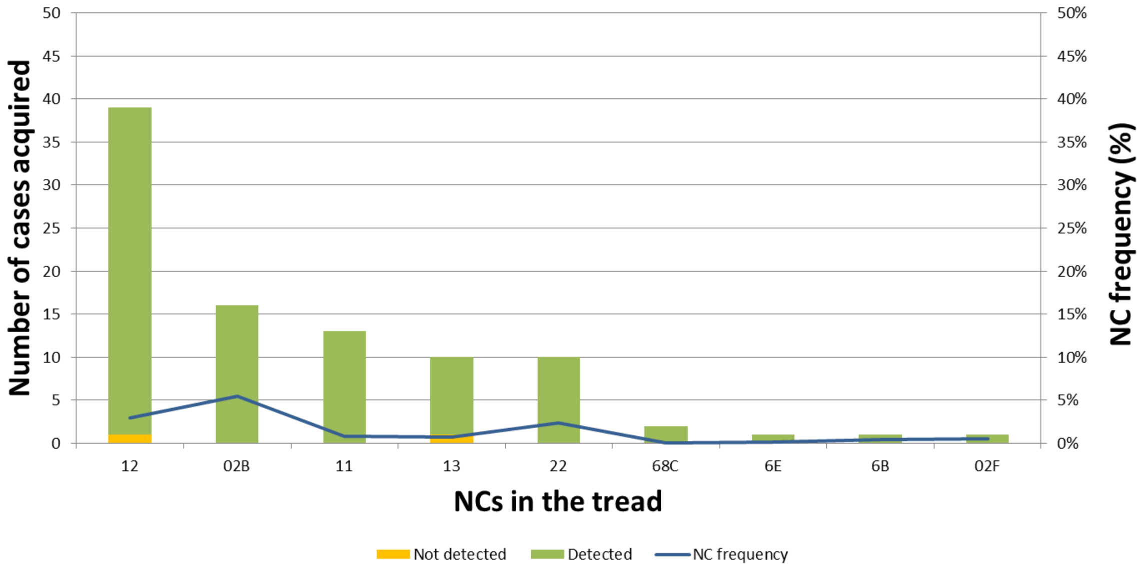


Figure 4.32 - For each NC in the tread the plot shows: the number of successful and unsuccessful validation cases and its frequency of occurrence in the past 6 months.

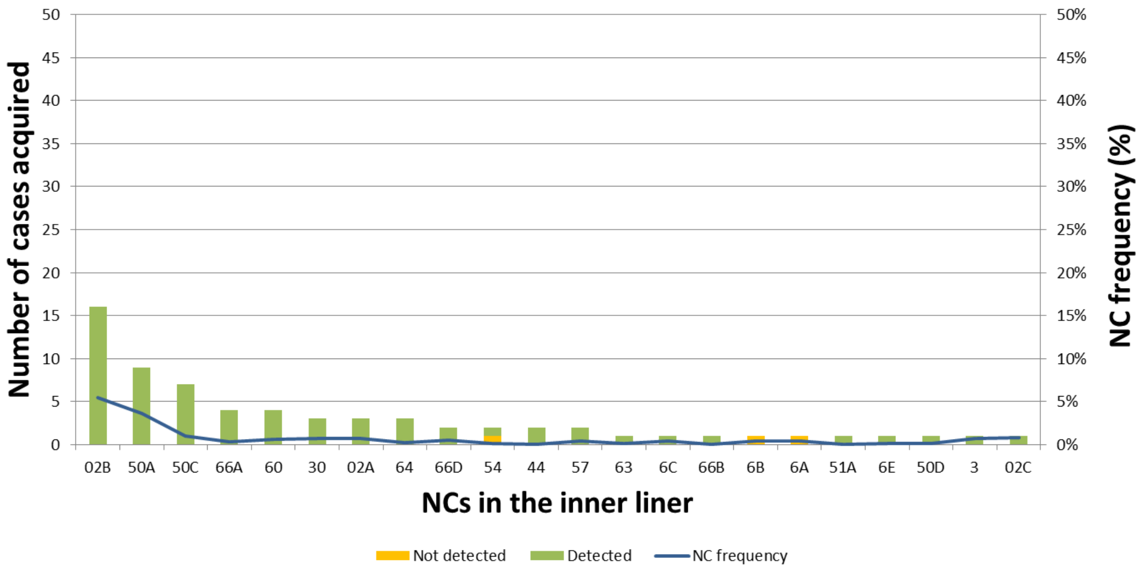


Figure 4.33 - For each NC in the inner liner the plot shows: the number of successful and unsuccessful validation cases and its frequency of occurrence in the past 6 months.

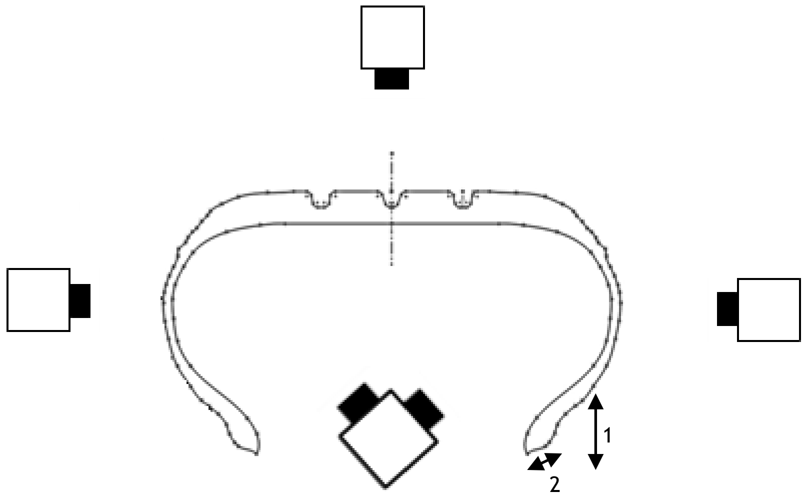


Figure 4.34 - Schematic of the final setup of cameras. The sidewall cameras also cover the acquisition of the bead area (1) but difficulties in adequately acquiring the bead edge (2) were noticed.

4.4 References

Al-Mallahi, A., T. Kataoka, H. Okamoto, and Y. Shibata. 2010. "An image processing algorithm for detecting in-line potato tubers without singulation." Computers and Electronics in Agriculture no. 70 (1):239-244.

Aluze, Denis, Fred Merienne, Christophe Dumont, and Patrick Gorria. 2002. "Vision system for defect imaging, detection, and characterization on a specular surface of a 3D object." Image and Vision Computing no. 20 (8):569-580.

Benmoussat, M. S., M. Guillaume, Y. Caulier, and K. Spinnler. 2013. "Automatic metal parts inspection: Use of thermographic images and anomaly detection algorithms." Infrared Physics & Technology no. 61 (0):68-80.

Blasco, J., N. Aleixos, S. Cubero, J. Gómez-Sanchís, and E. Moltó. 2009. "Automatic sorting of satsuma (Citrus unshiu) segments using computer vision and morphological features." Computers and Electronics in Agriculture no. 66 (1):1-8.

Blasco, J., N. Aleixos, and E. Moltó. 2003. "Machine Vision System for Automatic Quality Grading of Fruit." Biosystems Engineering no. 85 (4):415-423.

Boukouvalas, Costas, Francesco De Natale, Giovanni De Toni, Josef Kittler, Radek Marik, Majid Mirmehdi, Maria Petrou, Phillip Le Roy, Roberto Salgari, and Gianni Vernazza. 1998. "ASSIST: automatic system for surface inspection and sorting of tiles." Journal of Materials Processing Technology no. 82 (1–3):179-188.

Brosnan, Tadhg, and Da-Wen Sun. 2002. "Inspection and grading of agricultural and food products by computer vision systems—a review." Computers and Electronics in Agriculture no. 36 (2–3):193-213.

Chuang, Shui-Fa, Wen-Tung Chang, Chih-Cheng Lin, and Yeong-Shin Tarng. 2010. "Misalignment inspection of multilayer PCBs with an automated X-ray machine vision system." The International Journal of Advanced Manufacturing Technology no. 51 (9-12):995-1008.

Coulot, Claudine, Sophie Kohler-Hemmerlin, Christophe Dumont, Denis Aluze, and Bernard Lamalle. 1997. Lighting study for an optimal defects detection by artificial vision.

Davies, E. R. 2012a. "Chapter 20 - Automated Visual Inspection." In Computer and Machine Vision (Fourth Edition), edited by E. R. Davies, 525-552. Boston: Academic Press.

Davies, E. R. 2012b. "Chapter 25 - Image Acquisition." In Computer and Machine Vision (Fourth Edition), edited by E. R. Davies, 718-741. Boston: Academic Press.

Geveaux, Pierre, Sophie Kohler, Johel Miteran, and Frederic Truchetet. 1998. Searching method for an optimal lighting application for defect detection by artificial vision in industrial field.

Golnabi, H., and A. Asadpour. 2007. "Design and application of industrial machine vision systems." Robotics and Computer-Integrated Manufacturing no. 23 (6):630-637.

Guzmán, Elena, Vincent Baeten, Juan Antonio Fernández Pierna, and José A. García-Mesa. 2013. "Infrared machine vision system for the automatic detection of olive fruit quality." Talanta no. 116 (0):894-898.

He, Xiao D., Kenneth E. Torrance, François Sillion, and Donald P. Greenberg. 1991. "A comprehensive physical model for light reflection." SIGGRAPH Comput. Graph. no. 25 (4):175-186.

Herrero-Langreo, Ana, Loredana Lunadei, Lourdes Lleó, Belén Diezma, and Margarita Ruiz-Altisent. 2011. "Multispectral Vision for Monitoring Peach Ripeness." Journal of Food Science no. 76 (2):E178-E187.

Hornberg, Alexander. 2006. Handbook of Machine Vision: Wiley-VCH.

Kumar, A. 2008. "Computer-Vision-Based Fabric Defect Detection: A Survey." Industrial Electronics, IEEE Transactions on no. 55 (1):348-363.

Liu, J. Jay, and John F. MacGregor. 2005. "Modeling and Optimization of Product Appearance: Application to Injection-Molded Plastic Panels." Industrial & Engineering Chemistry Research no. 44 (13):4687-4696.

Malamasa, Elias N. , Euripides G.M. Petrakisa, Michalis Zervakisa, Laurent Petitb, and Jean-Didier Legatb. 2003. "A survey on industrial vision systems, applications and tools."

Mian, Ajmal, and Nick Pears. 2012. "3D Face Recognition." In 3D Imaging, Analysis and Applications, edited by Nick Pears, Yonghuai Liu and Peter Bunting, 311-366. Springer London.

Molleda, Julio, Rubén Usamentiaga, Daniel F. García, Francisco G. Bulnes, Adrián Espina, Bassiru Dieye, and Lyndon N. Smith. 2013. "An improved 3D imaging system for dimensional quality inspection of rolled products in the metal industry." Computers in Industry no. 64 (9):1186-1200.

Pernkopf, Franz, and Paul O'Leary. 2003. "Image acquisition techniques for automatic visual inspection of metallic surfaces." NDT & E International no. 36 (8):609-617.

Rosati, G., G. Boschetti, A. Biondi, and A. Rossi. 2009. "Real-time defect detection on highly reflective curved surfaces." Optics and Lasers in Engineering no. 47 (3–4):379-384.

So, Edmond Wai Yan, Matteo Munaro, Stefano Michieletto, Stefano Tonello, and Emanuele Menegatti. 2013. "3DComplete: Efficient completeness inspection using a 2.5D color scanner." Computers in Industry no. 64 (9):1237-1252.

Tao, Yang. 1996. "Spherical transform of fruit images for on-line defect extraction of mass objects." Optical Engineering no. 35 (2):344-350.

Thomas, A. D. H., M. G. Rodd, J. D. Holt, and C. J. Neill. 1995. "Real-time Industrial Visual Inspection: A Review." Real-Time Imaging no. 1 (2):139-158.

Tian, Gui Yun, Rong Sheng Lu, and Duke Gledhill. 2007. "Surface measurement using active vision and light scattering." Optics and Lasers in Engineering no. 45 (1):131-139.

Valle, M. D., Paolo Gallina, and A. Gasparetto. 2003. "Mirror synthesis in a mechatronic system for superficial defect detection." Mechatronics, IEEE/ASME Transactions on no. 8 (3):309-317.

Wedowski, Raphael D., Gary A. Atkinson, Melvyn L. Smith, and Lyndon N. Smith. 2012. "A system for the dynamic industrial inspection of specular freeform surfaces." Optics and Lasers in Engineering no. 50 (5):632-644.

Wolff, Lawrence B. 1994. "Relative brightness of specular and diffuse reflection." Optical Engineering no. 33 (1):285-293.

Wordsworth, Saul 2008. "Defect-free production through sensor technology." Tire Technology International.

Yeh, Michelle, and Christopher D. Wickens. 2001. "Display Signaling in Augmented Reality: Effects of Cue Reliability and Image Realism on Attention Allocation and Trust Calibration." Human Factors: The Journal of the Human Factors and Ergonomics Society no. 43 (3):355-365.

Chapter 5
Experimental design for computer assisted inspection validation

Proposing a scenario in which the final inspection process is digitally performed by operators through CAI can only be done when proved that the operators are able to inspect tires digitally with a comparable quality level as the one obtained at the as-is manual process. Thus, the objective of this chapter is to understand if the visual inspectors are capable of inspecting tires by means of computerized images through CAI rather than using the physical object. A use of CAI system for the inspection process of tires that accelerates and optimizes operators' performance is being hypothesized.

As mentioned in the previous chapter, having the operators inspecting tires through CAI is an essential development step. In the development phase, CAI is in between two steps that require and benefit from operators' validation. Inspectors through CAI validate the appropriateness of the images acquired (upstream process) and assign a quality decision based on the images, essential for the development and validation of automatic quality inspection (downstream process). These interrelations motivated the implementation of AutoClass database that stores the parameters of each step (image acquisition, CAI and automatic quality inspection). Besides image acquisition parameters such as lighting conditions, mechanical system set-up, etc., at CAI, the decision of the operator, the location of imperfections, if existent, and cycle time, are stored for all assessments done by the operators. The control and analysis of these parameters permit the definition of improvement strategies across the whole system.

The results obtained along this research, together with the operators' positive feedback, support the hypothesis that CAI may be more than a validation tool. It can (and should) be an integral component of the proposed inspection solution. In this scenario, the system will include operators' participation at CAI so that they decide tires' quality level in cases in which the algorithms were not conclusive. The use of the human extensive knowledge and flexibility in decision criteria supports this system design.

Thus, the potential advantages of CAI go beyond its role as validation step. As an integral part of the proposed inspection process, CAI presents many advantageous characteristics over the current inspection process that potentially can:

- Reduce physical workload – operators would not need to perform tire handling;

- Lower average inspection time – by eliminating tire handling steps and by the use of image processing techniques as a decision support system that restricts the information that need to be analyzed by the operator;
- Reduce variability in inspection time – concentrate the operators in the decision selection may reduce many factors that today contribute for significant cycle time variability;
- Provide more uniform visualization conditions across tire areas – high resolution images of all tire surfaces improve the observation conditions;
- Facilitate feedback to operators – contrary to today's process, in which the operators receive very limited feedback about their decisions (only limited feedback is provided by overinspector), the storage of images and decisions enables the recall of past decisions and the associated images.
- Continuous learning and customized training sessions – The previous point can also contribute to the definition of a program of continuous improvement and training tailored to each operator, based on their past decisions' profile.

CAI can also bring benefits to the organization as a whole. The fact that images of all produced tires are being stored, as well as the quality decisions associated to them, makes information more accessible in case of complains. Also, inspection can be performed at CAI by more than one operator for more demanding customers or more critical tire articles, resulting in an increase in the confidence level of the decision. Finally, CAI can also be used to generate quality alerts that enable quicker reaction times when corrective actions along the manufacturing process are needed.

Some of the potential advantages described before were tested by means of a set of field experiments done with the participation of the operators. The objective is to evaluate the effectiveness of CAI as vehicle of information. Images acquired at the image acquisition station were organized in sessions and made available to operators. Contrary to the previous chapter, in which the operators knew beforehand that the images were non-conforming and the code associated to each, in the tests described below random images are shown with no hint about quality state. The objective is to evaluate their detection and decision capabilities in the proposed digital environment. Guaranteeing at least the same quality level as in today's process is essential to validate CAI as a novel inspection method.

5.1 Computer assisted inspection: Design and validation

As mentioned in the previous chapter, operators at CAI interact with an application that displays tire images. The user interface was developed aiming at being: intuitive, user friendly and reliable. An additional study in the context of this project assessed the requirements of the interface and tested different visualization alternatives. The one described in this document achieved higher performance results.

Images are shown statically since moving images can originate some blurring effects (Brown, Dismukes and Rinalducci 1982). Only one image is shown at a time, representing a certain tire region (sidewall, tread, inner liner). Because the images are acquired in a sequential mode they are much longer in width than in height. The images are displayed at the highest resolution and this usually leads to a subdivision of the image in more than one section. Each section is shown at a time. With the mouse, the operators, moves the sub-image forward or backwards to visualize the entire image. Some overlap on the left and right of each subdivision is essential to avoid misses in the transitions.

The step of visual search in CAI is significantly different to the one performed by the operators at the current inspection workplace. While today the tire is rotating and the operator typically fixates a point and detects artifacts that pop-up during the rotational movement, CAI system requires a sequence of eye fixations. Because the images are static in the display, the operators need to move the central vision to scan the entire image. This suggests that, although tire images are as similar as possible to the real object (assured by the machine vision technology selection described in Chapter 4), the mechanism of visual search is significantly different in CAI. This motivated the training sessions but an accurate estimation of the time needed for the operator to shift the visual search strategy is not easy to be done. A miss-adaptation might still affect the results described below.

The fact that the images are acquired in a linear mode results in flat images representing an intricate 3D object. Reducing the complexity of the object displayed and dealing with its complex shape at the level of the image-acquisition station was the strategy defined.

The research method selected to validate CAI system is an experimental field study in which a group of operators will assess a sample of tires at the current inspection workplace (control group) while a second group will inspect the same sample through CAI (experimental group). The objective is to understand the effect of CAI environment (independent variable) on the quality detection performance of operators (dependent variable). Later in this chapter a comparison between the performances of the two groups is shown.

5.2 Experimental Design

A posttest-only control group trial was conducted comparing the detection rates of two groups of operators. This experimental design is suggested in the literature for assessing cause-effect relationships (Greenberg et al. 2008; Babbie 2010; Campbell and Stanley 1973). Campbell and Stanley (1973) suggested the following diagram to describe posttest-only control group experimental design:

$$\begin{array}{ccc} R & X & O_1 \\ R & & O_2 \end{array}$$

R are the groups to which separate treatments will be assigned. X represents the exposure of a group to the experimental variable, whose effects will be measured. O refers to the process of observation or measurement. In a posttest-only controlled trial, no measurement is done before the experiment. Rather, the random selection of participants is expected to minimize the effect of unknown individual differences.

In the context of this research, the first group (experimental group) will perform inspection at CAI (X) while control group will inspect tires by means of the current manual process. The independent variable in the experiment is the use of CAI while the dependent variable will be the binary quality assessment (OK or NOK).

As described in Chapter 2 there is a significant variability in the average inspection time and rejection rate among inspectors. For this reason, historical data of a one-month period was analyzed so that operators with equivalent rejection rate and productivity could be assigned to the two groups. Avoiding, for example, that only risk averse operators (profiles with higher rejection rates) are assigned to CAI or manual inspection is desirable. Thus, the allocation of operators to the experimental group and control group will be done with the objective that both groups individually match in terms of average productivity and rejection rate. After grouping the operators in terms of their profile, their selection and allocation to each of the two groups was randomly done. This intends to minimize the possibility of selecting biased groups. A total number of 12 operators participated in this study. 6 operators were assigned to the control group and other 6 to CAI in which they were previously trained.

This experiment occurred during a 2-month period at Continental Mabor manufacturing plant. Images of 1000 tires were acquired. This sample of tires is representative of a random sample and, therefore, approximately 90% of them were OK tires. The remaining 10% contain imperfections. From the 76 different NC codes, 41 were represented in this sample. The non-conforming tires selected for this sample also vary in terms of severity.

Every day, 40 tires were collected and sent to the image acquisition station (4 NOK and 36 OK to keep usual conditions). Each day, 12 operators assessed the 40 tires. The image acquisition step occurred in one shift and the assessments by the operators at the following one (Figure 5.1).

This experimental design originated a significant volume of data that was stored in AutoClass database. A total of 6,000 digital assessments were compared to an equal number of as-is inspections. Various data was stored during the tests. At CAI, there was an automatic storage of the binary assessment (OK or NOK) and imperfection location (in case of a NOK assessment). Also the time of inspection was automatically stored. At the as-is process it is not possible to store the location of imperfection but the overall decision was recorded. Also inspection time was measured.

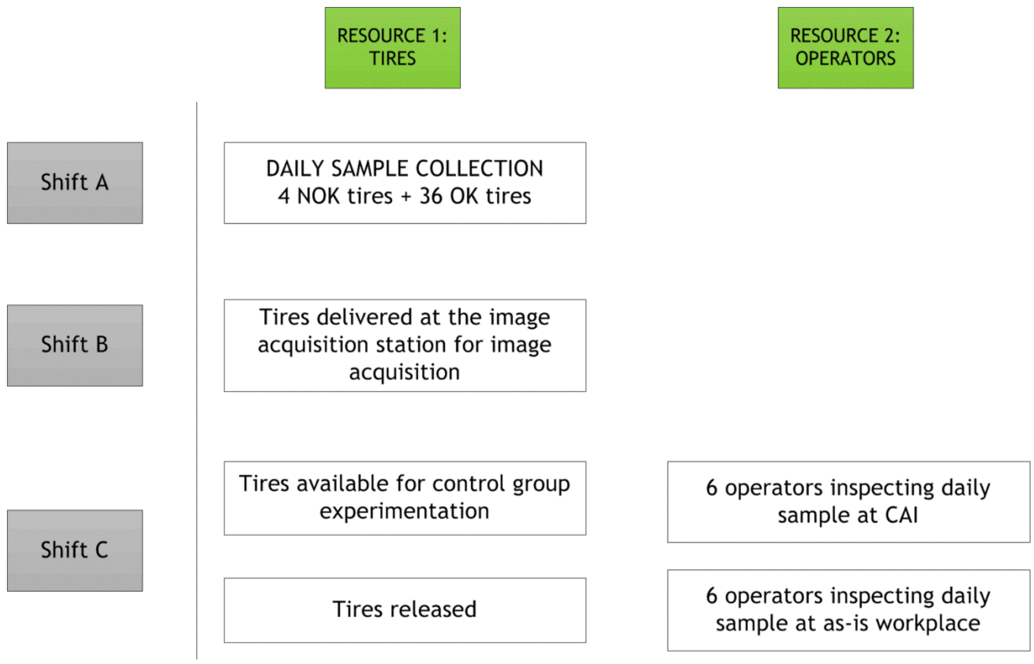


Figure 5.1 - Operationalization of the experiment.

5.3 Results

Because the only matching criterion was keeping operators with equivalent average inspection and rejection rate in both groups, the random selection led to the participation of operators with many different profiles regarding age, years of job experience and education. For the benefit of the experiment documentation, these indicators were obtained through a questionnaire in the beginning of the study. As an example, one operator selected was 54 years old at the time of the experiment presenting 15 years of experience, while another was 29 years old and had been in the job for 1 year. Enrolling operators with such different profiles in this study, contributed to its relevance.

The quality decision made by the two groups is the main dependent variable. As mentioned before, the current manual inspection process does not allow for the recording of the imperfection location. Thus, the comparison of quality assessments was made considering binary decisions. Both groups' quality decisions were compared to the one registered at the image acquisition station. The tires selected for this sample were segregated and classified by the graders. Thus, graders assign the reference decision, always assumed as correct.

Operators were very enthusiastic about participating in this study. They were very collaborative and participative along the research. To keep their interest along the experiment and to contribute to a faster learning curve for the experimental group, individual feedback sessions were organized on a weekly basis. At the feedback session, a report would be given to each one demonstrating their quality performance and inspection time for the sessions performed in the previous week. For the operators belonging to the experimental group, the images in which they failed were shown to them, together with an explanation of the correct decision for each case.

The consolidated results obtained through the abovementioned experimental design are plotted in the gray and yellow series in Figure 5.2. The results were obtained across the 25 testing sessions. The control group presents a higher accurate detection rate over the experimental group (the control group's performance in terms of correct decisions is higher than the experimental group's one by 18%). Experimental group also revealed a higher false positive and miss rate. The results are not shown in a discrete manner for each session because no time dependent pattern was noticed.

Many factors may influence these results but the most probable one is the need of a more intensive training program and longer adaptation period. The results obtained in Chapter 4 in which the operators were able to accurately identify 97% of the NC locations when given its code, reveals that the images are appropriately acquired and that the operators are able to interface with them. When performing the quality assessment through CAI independently and in a random mode, operators lowered their performance, suggesting that their adaptation to the method needs further attention. In fact, moving from a shop floor workplace to a computerized one, requires many adaptations and development of mechanisms to deal with a sedentary job that requires more cognitive processing and mental attention (Brown, Dismukes and Rinalducci 1982; Mocci, Serra and Corrias 2001). It is also important to notice that the relative importance of each of the three considered classes (correct decision, miss and false positive) is the same for both groups which denotes a general underperformance and not a specific error type.

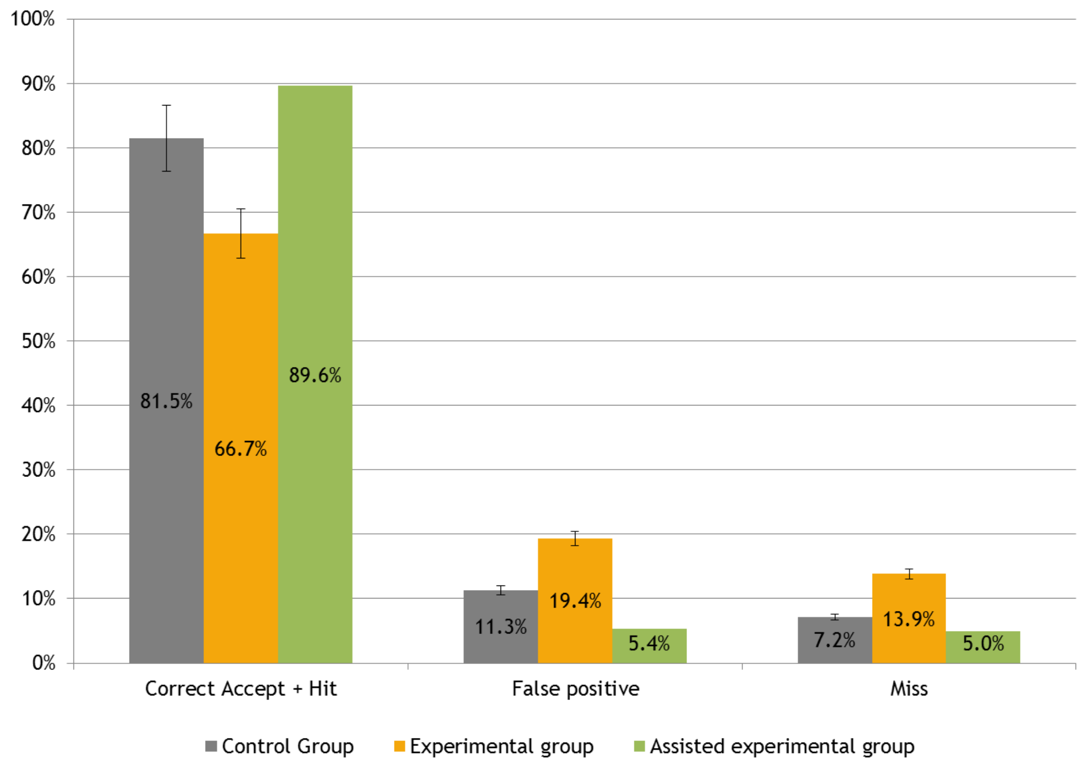


Figure 5.2 - Performance comparison between control group, experimental group and assisted experimental group.

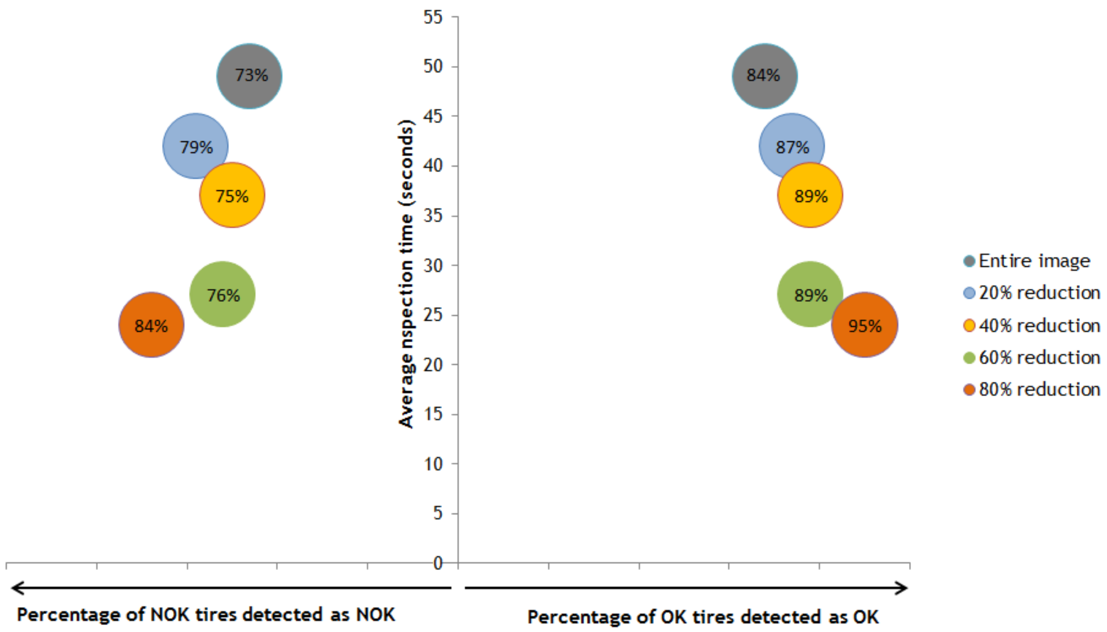


Figure 5.3 - Relation between area shown to operators and performance indicators (quality detection and inspection time).

After concluding the research experiment, additional tests involving CAI were performed. Although the automatic detection algorithms are not yet integrated with CAI, the analyses of their impact as assisting tool is of interest. Thus, for a smaller sample of 100 tires (the change in sample size was due to limited operators extra availability), eight additional sessions were created in which the operators received only part of the tire image (Assisted-CAI), as to emulate the process when an online connection between automatic inspection algorithms and CAI is in place. The eight new sessions were distributed along 4 scenarios of reduced inspection area: 20%, 40%, 60% and 80% of the images' area were removed. The results of these tests are presented in Figure 5.3. In this plot, the correct assessments are represented, keeping NOK tires to the left and OK tires on the right. Ideally the circles would be on the external edges, showing 100% of correct decisions. The lower they are on the vertical axis, the lower the inspection time. Starting from the top, a series in which the complete image was made available to inspectors is displayed (Experimental Group). This shows a high inspection time compared to the control group (48 seconds vs. 29.6 seconds of control group). An improvement in both these variables (correct decision percentage and inspection time) is noticeable as the percentage of image conveyed to inspectors is reduced. A 40% reduction in image size results in a reduction of inspection time by approximately 12 seconds (25%) and increases the correct evaluation by 2% in NOK tires and 5% in OK tires. By doubling the percentage of reduction in image size (to 80%), the reduction on inspection time becomes 52% lower (becoming lower than the current manual inspection time) and the improvement in correct decisions is 11% for both OK and NOK tires. A representation of the outcome of a process considering 80% reduction in image size is represented in green in Figure 5.2. By implementing a step that, using automatic algorithms, manages to reduce the area of images displayed to operators to 20% that might contain NCs, CAI manages to outperform the control group in all the classes of Figure 5.2 and also in the inspection time.

Figure 5.4 compares the performance of the three inspection scenarios. The plot of the hit rate as a function of the false positive rate is known as the *relative operating characteristics* diagram (Sylla 2002). Each point in the plots is the result of an operator session performance. The upper left corner represents perfect results in which all conforming tires are assessed as OK and non-conforming ones as NOK. In this case, the closer the operators are from the upper left corner, more correct their decisions are. The advantageous of this visualization mode is the possibility to understand system evolvements. Having the upper plot in Figure 5.4 as the reference control group, the second plot shows the decrease in performance and higher scattering, associated to CAI (Experimental group). This may suggest that operators were still not adapted to CAI methods. Finally, the last plot shows a recover in operators' performance, obtained by reducing the area to be inspected to 20%. Data is much more concentrated on the top-left quadrant and reveals that operators are able to perform similarly to the current manual inspection (refer to RQ 1.2 in Figure 1.2).

According to a parallel work developed in this project, cost projections were established as a function of inspection time. The number of human resources required varies linearly with the cycle time to inspect each tire. As mentioned in Chapter 3, human resources account for 70% of inspection costs. By lowering the inspection time, costs can be reduced. As abovementioned, results depicted the need of further familiarization of operators with CAI. Therefore it is fair to estimate that, by addressing the operators' training needs more carefully, CAI times may be further reduced, thus translating into inspection costs decrease.

These results show the need of reliable algorithms capable of automatically assessing the conformity of tires, and reduce the area that requires human inspection. This will be the subject of the next chapter.

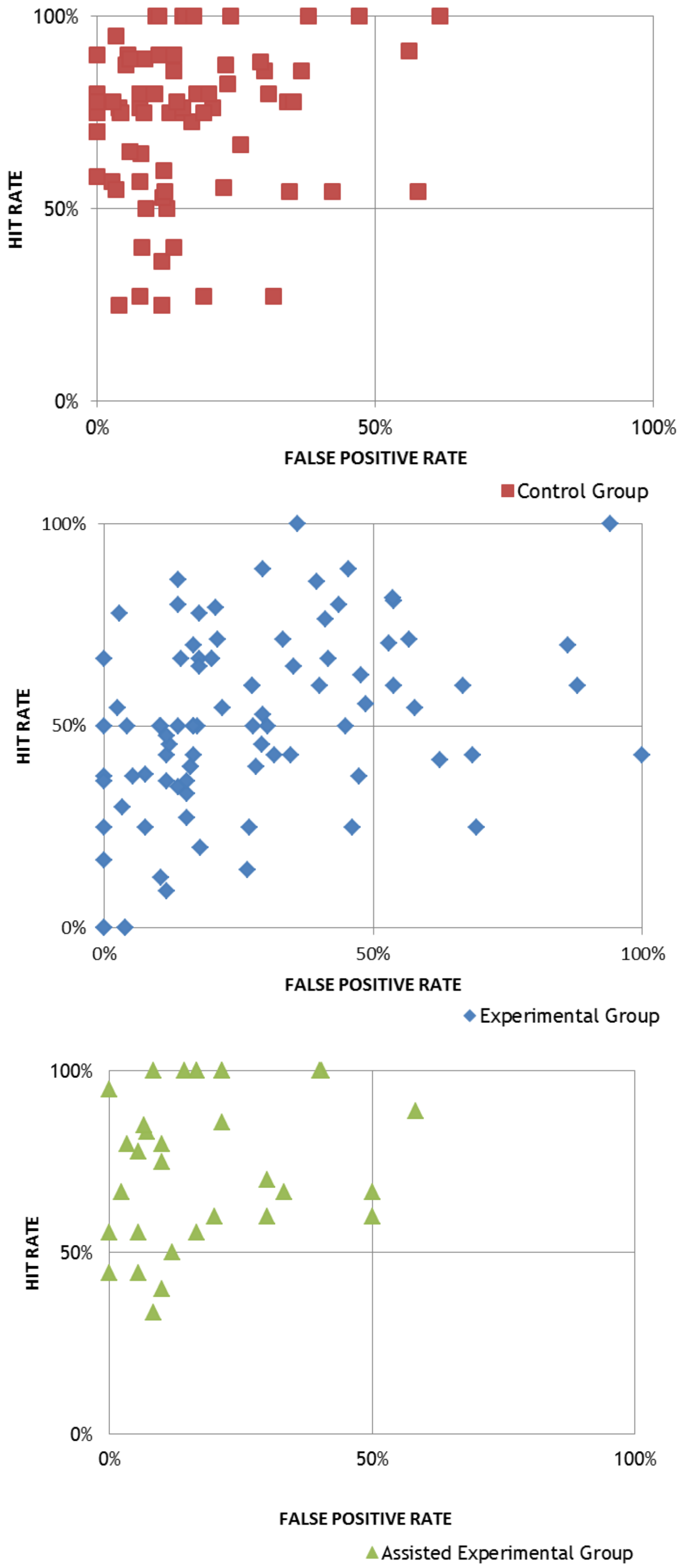


Figure 5.4 - Performance of the various inspection scenarios: Control group (manual inspection), Experimental Group (CAI), and assisted Experimental Group (Assisted CAI).

5.4 References

Babbie, Earl. 2010. The Practice of Social Research. 12th ed. Belmont, USA: Wadsworth.

Brown, Barbara S., K. E. Y. Dismukes, and Edward J. Rinalducci. 1982. "Video display terminals and vision of workers Summary and overview of a symposium†." Behaviour & Information Technology no. 1 (2):121-140.

Campbell, D., and J. Stanley. 1973. Experimental and Quasi-experimental Designs for Research: R. McNally College Publishing.

Greenberg, C. , R. Diaz-Flores, S. Lipsitz, S. Regenbogen, L. Mulholland, F. Mearn, S. Rao, T. Toidze, and A. Gawande. 2008. "Bar-coding Surgical Sponges To Improve Safety." Annals of Surgery.

Mocci, F., A. Serra, and G. A. Corrias. 2001. "Psychological factors and visual fatigue in working with video display terminals." Occup Environ Med no. 58 (4):267-71.

Sylla, Cheickna. 2002. "Experimental investigation of human and machine-vision arrangements in inspection tasks." Control Engineering Practice no. 10 (3):347-361.

Chapter 6
Methods for automatic quality assessment of tires

The objective of this chapter is to demonstrate that image processing techniques can be reliability applied to the detection of imperfections in tires. In the context of this project, developing automatic detection algorithms firstly aims at guiding visual attention of operators to potential defective areas. The use of automation for attention guidance is successfully being used in military, aviation and medical domains (Kirlik 2009; Cummings 2004). Fully automatic decisions will be a consequence of a continuous improvement and demonstration of algorithms reliability.

Automatic detection algorithms are suggested as a mechanism to accelerate inspection but, while accurate fully automatic decision is not assured for all possible imperfections, they can be used to enhance the information displayed in CAI. This intermediate step is advantageous for many reasons. First, from the development perspective, it is crucial that, before attempting to automatically detect imperfections, the machine vision system is validated in terms of accurate acquisition of imperfections. To attempt to automatically detect an imperfection, there must be some sort of contrast between its shape and the background, thus the shape can be said to exist. As a consequence, if an imperfection is not represented in the image, no algorithm will be capable of its detection (evidences on this are shown in Chapter 4). No one better that the visual inspectors can assess how accurate the representation of imperfections in the images is. Secondly, the CAI step allows the storage of assessments performed by operators. These are essential for the subsequent step that involves the development of the automatic detection algorithms. As mentioned in Chapter 2, not always the rejection criteria are accurately defined and again no one better that the inspectors can provide inputs for the development of automatic detection techniques. Finally, an analysis from the company perspective, demonstrates that there are significant economic benefits in the CAI. This achievement is crucial to guarantee a sustainable development of automatic detection algorithms. The system can be implemented at first with a lower LOA that should be increased along time.

As mentioned in Chapter 2, humans are known for being furious pattern matchers, able to perform visual search by recalling how a conforming item should look like and detect whatever “pops out” differently. In fact, humans are extremely good at making rapid assessments of complex situations based upon matching features of the world to similar situations stored in long term memory. Particularly in the inspection of tires, operators use this ability because the vast number and shape variety of imperfection is not compatible with a strategy of visual searching for each one individually. The operators frequently mention that they do not attempt to discover imperfections; rather they are expecting that imperfections will be visible as a sudden variation from the regular background.

The development of the automatic detection algorithms proposed in this dissertation followed a similar strategy by attempting to maintain equivalent abilities and similar criteria. For this reason, the process of automatically detecting imperfections is related with a general field of image processing called template matching. Template matching has been used in robotic applications, video surveillance and industrial inspection (Crispin and Rankov 2009). In defect inspection applications, the similarity measure between two images, one to be inspected and a faultless second, is calculated (Tsai and Yang 2005). The task of surface defect detection is generally a qualitative method in which the presence or absence of a visually faulty item determines the final quality assessment. The fact that defective regions typically imply changes in intensity due to uneven illumination or irregular texture pattern is normally the starting point for the development of automatic detection algorithms (Tsai et al. 2012).

Like image acquisition, the determination of the adequate algorithms for tire quality inspection is not straightforward, due to its particularities. The adjustment of the mechanical system position (to minimize vibrations) and lighting configurations (to highlight imperfections) according to the tire allow for image acquisition in a more stable and repeatable manner. Despite this fact, intrinsic tire characteristics and imperfections' variability constrains the applicability and performance of some image processing algorithms for quality assessment. Specially for being a deformable object, the complexity of the tire automatic quality control is significant and led the development of novel algorithms. This difficulty seems to be common to other industrial applications. Some studies report that improving algorithms robustness should keep up with the continuous development on vision sensors, otherwise they will be the limit to the penetration of machine vision for quality control into industrial scenarios (Bozma and Yalçın 2002).

In every engineering design exercise, there are numerous factors specific to the task in hand. Tire inspection is an application particularly challenging for automatic quality assessment with specific requirements due to: variable surface properties, deformable shape, and imperfections varying stochastic in scale, stretch and skew.

6.1 Image processing techniques for quality assessment

The mechanisms used by automatic algorithms and humans in image interpretation are significantly different. Automatic algorithms are expected to minimize some effects of misleading human perceptions of shapes and colors. Despite the fact that the eye is an excellent detecting system, the data elaborated by the brain do not always give a correct perception of the object (Di Lazzaro, Murra and Schwortz 2013). Patterns and colors may be perceived in a subjective way. What humans perceive as a definite color is, in fact, the consequence of the comparison between the object and its context. This can lead our eye-brain system to be fooled as shown in Figure 6.1, which shows the ''checker shadow illusion''. In this image two identical gray squares appear different just because they are surrounded by different square colors, and the presence of a shadow enhances the illusory effect. The eye-brain system cannot perceive the absolute lightness of square A and B but rather relative lightness (Robinson, Roodt and Nel 2012). The incorrect perception of reality is independent of the individual will, and the response of eye-brain system is almost the same for all humans. In examples such as this, digital imaging processing techniques should be used as assisting tools or as stand-alone methods.

Surface defect inspection is a typical quality control process in manufacturing for materials containing non-textured or textured surfaces. The detection algorithms applied in both differ. Defect detection in non-textured materials (such as metals, film, paper, etc.) relies upon identification of regions that differ from a uniform background. Morphological operations, analysis of local intensity discontinuities and gray-level statistical methods are techniques typically used to detect and identify a large variety of surface flaws on metallic objects such as: scratches, dents, dirt, and corrosion (Zheng, Kong and Nahavandi 2002; Pernkopf and O'Leary 2002).

Another group of surfaces that can be inspected automatically are textured materials. The textured materials can be further divided into uniform patterned or random textures (Figure 6.2). In uniform patterned textures such as fabrics, sandpaper, leather; the occurrence of a defect means that the regular global structure has been destroyed. In this application, the frequency spectrum is typically analyzed by means of Fourier transformation for detecting structural defects. Several studies suggest Fourier transform because it reveals a well-known shape with peaks whose location depends on the spatial frequencies of yarns (Castellini et al. 1996; Chi-Ho and Pang 2000).

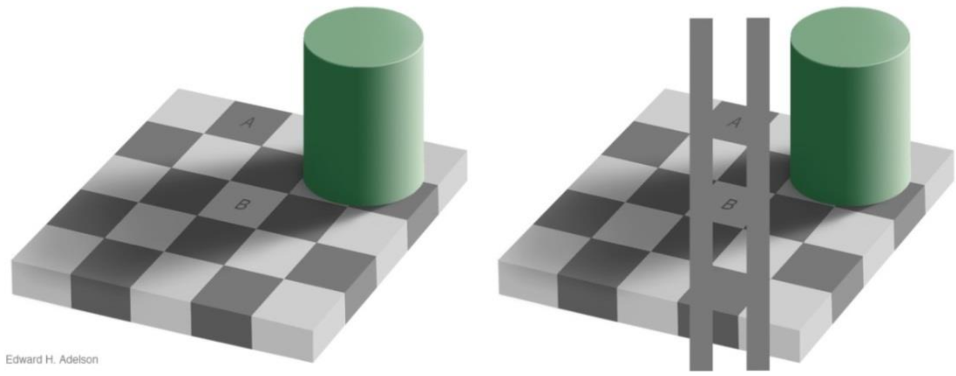


Figure 6.1 - The Checker Shadow Illusion: On the right, proof that square A and B have identical intensities (Adelson 2000).

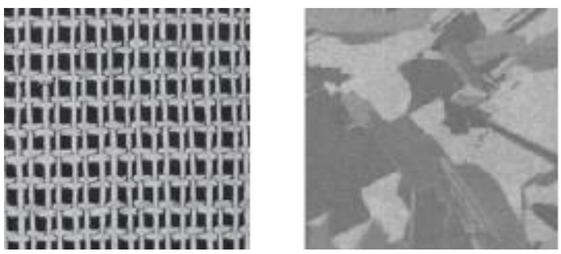


Figure 6.2 - Examples of textured materials. The images show: on the left an uniform textile pattern and on the right a random pattern in a solar wafer ((Nixon and Aguado 2012a; Tsai, Chang and Chao 2010).

Applications involving heterogeneous texture patterns require more sophisticated image processing techniques. Studies in the field of solar wafers inspection are an example of a random texture in which the crystal grains present random shapes, sizes and directions (Li and Tsai 2011). The use of anisotropic diffusion-based methods was validated for micro-crack detection (Tsai, Chang and Chao 2010). By adjusting the diffusion coefficients, the contours of the defects can be enhanced while intra-regions become smooth. Shin-Min et al. (2006) also suggested and demonstrated the used of anisotropic diffusion to detect defects in the glass substrates surface.

Tires are definitely not a non-textured object. Nevertheless, framing the tire texture in one of the abovementioned categories is not trivial. Although tire texture is known (sidewall lettering, tread pattern, etc.) it does not present a periodical, repetitive pattern. Rather each surface has its own design and features. For this reason, tire cannot also be classified as heterogeneous, although there is some random component about its shape due to its deformable properties.

Regarding the image processing techniques mentioned above, limited applicability in the tire application is envisaged. Because methods based on Fourier transform exclusively characterize the spatial-frequency distribution, they are mostly tailored to texture patterns that are approximately identical everywhere in the inspection image. The periodic and repetitive pattern can be removed using the inverse Fourier transform, after which the homogeneous region in the original image will have an approximately uniform gray level, and yet the defective region will be distinctly preserved. This converts the difficultly in defect detection in uniform textured images into a simple threshold problem in non-textured images (Tsai and Huang 2003). In the tire application, texture grooves, embossments and letterings significantly change the uniform gray-level of the tire. The intensity variation in these faultless textured regions can be on the same range as gray-level variations caused by defective regions. Distinguishing the causes for intensity variation cannot simply be done as in fabric quality inspection application, in which authors simply suggest setting up upper and lower control limits for distinguishing defects from the uniform background (Tsai and Huang 2003). Also, the applications suggesting anisotropic diffusion are based on intensity unique features of defects. Authors highlight the need that defects present both dark intensity and high contrast in the sensed image, which tailors this method only to specific imperfections and applications (Tsai, Chang and Chao 2010). There are many other image processing techniques and transforms described in the literature for texture characterization. The wavelet transform, for example, is a very popular method (Nixon and Aguado 2012b). Although improved detection capabilities were described when comparing to Fourier transform, most studies also rely on the elimination of regular and repetitive texture patterns by selecting proper smooth or detail sub-images for wavelet synthesis (Tsai and Chiang 2003; Ngan, Pang and Yung 2011).

Differently from many studies mentioned before, the imperfections that can occur in tires vary significantly in shape and intensity. While some are highlighted by its brighter intensity others do become noticeable for being darker. Furthermore, a spatial-analysis based on intensity profiles may not be able to distinguish them from other features that also originate intensity variations. For this reason, the development of automatic detection algorithms for tire quality inspection was mostly focused on broader techniques not specific for a certain imperfection type. Similarly to the manual inspection process, the automatic detection does not intend, at least in this stage, to fully characterize the imperfection type and its dimension. Rather the approach would be to reject a tire that contains an abnormal feature. In the literature, this strategy is typically addressed by template matching algorithms.

Template matching is one fundamental technique occurring in countless image analysis applications (Sarvaiya, Patnaik and Bombaywala 2009). This technique aims at locating a given template into a reference image by means of subtractions methods. This task consists on determining the regions of the image under assessment that are *similar* to the template according to a given criterion and discarding those that are *dissimilar* (Tombari, Mattoccia and Di Stefano 2009). The basic template matching algorithm consists in calculating at each position of the image under assessment the degree of similarity between the template and the image (Sarvaiya, Patnaik and Bombaywala 2009). Different metrics or measures have been proposed to define the similarity between the two images. There is not a single similarity measure that is known to produce the best result in all situations. Depending on the application in hand measures such as sum of absolute differences, sum of squared differences or geometric distance can be considered (Ding, Goshtasby and Satter 2001).

Template matching is the general terminology of a technique that is found in the literature applied in many different ways. Categorizing template matching can be done by the source of the reference image. Based on that it can either be: referential image or CAD (Computer-Aided Design) based comparison (Newman and Jain 1995a). The first approach involves matching a template of a defect-free image acquired in the same scene (Nixon and Aguado 2012a). In the second case the comparison is based on a CAD model. Authors suggest the use of CAD models in inspection because the models contain an exact specification of an ideal part. But variances in the production process make it impossible to build a part in exact accordance with the specifications, which leads to the establishment of tolerances (Newman and Jain 1995b; Moganti et al. 1996). Nevertheless, authors refer that the limitation of this technique (independently of the source of the reference) is the number of rejections due to normal manufacturing distortions (Moganti et al. 1996; Ngan, Pang and Yung 2011). Avoiding this may be done by introducing large and variable tolerance ranges but this can lead to imperfection misses (Enzberg and Michaelis 2012). Authors highlight the difficulties in applying template matching techniques particularly to images that may contain specular reflections and curved surfaces (Newman and Jain 1995a).

Tires contain curved surfaces and possibly specular reflections, but the most challenging aspect in applying template match techniques to tires' quality assessment seems to be its flexible shape. As mentioned by Enzberg and Michaelis (2012), adjusting the template match method to account for tolerance ranges and possible deformation is difficult or in many cases impossible. Some methods suggest the use of several measurements of typical faultless sample surfaces to describe a defect-free part. Lilienblum et al. (2000) described a study based on the strategy of using several faultless samples. This study is limited to the detection of one specific defect in car bodies that for presenting a significant height variation lead to the use of 3-D measurement methods. The high stretchability of knitted fabrics also motivated the development of automatic quality control strategies able to deal with distortions and deformations. The authors developed a system that involves a line-by-line tracking of the live lace image and its match to the perfect prototype. Subsequently adjustments to the live image lines to correct any lateral, longitudinal or skew distortions are done (Farooq et al. 2004).

6.2 Proposed algorithms

Analysing the literature gives the notion that tires present characteristics that put them amongst the most complicated objects to be inspected automatically. Normally each study attempts to find alternative methods to deal with a particularity derived from a certain application. This particularity can be reflective surfaces, deformable materials and intricate geometries that require specific methods. As mentioned before, tires present all these aspects at once, which denotes how challenging the problem is. This renders the applicability of direct comparison methods, such as those employed for the automatic inspection of printed circuit boards and metallic parts. They would lead to unacceptable levels of false positives. Thus, template matching techniques cannot be applied in a straightforward manner and novel contributions were made.

Before describing the strategies defined for automatic quality inspection, a section about automatic tire identification is given. Tire identification is part of the tasks performed by the visual inspectors that is hypothesized to benefit of an increased LOA. This step is essential in the production flow for tracking purposes. Additionally its methods also provide outputs needed for the subsequent task of automatic quality inspection. After this, the methods developed and applied for the automatic detection of imperfection in tires are described and validated.

6.2.1 *Tire identification*

As mentioned in Chapter 2, tire identification is a task performed by visual inspectors at the current quality control process. This task intends to unequivocally identify the tire article being inspected considering that in the previous process (vulcanization) a single green tire can originate several different cured tires. For being a very repetitive and non-cognitive demanding task, in Chapter 3, tire identification was proposed as an optimal candidate to have automatic methods applied to. Tire identification involves two sub-tasks: identification of DOT and mould (i) and color line (ii). DOT and mould are alphanumeric codes that are embossed in the sidewall. Color lines are painted along the tread. Both DOT code and color lines correspond to a specific green tire code. They are automatically verified for redundancy purposes and to track possible printing inconsistencies. The mould number identifies the cavity in which the tire was cured. For this reason, the identification of this element is mandatory.

The strategy to perform a comparison between a reference image and a new sample requires that, from all tire articles that will be assessed, at least one acquisition of a conforming case must be done. While performing the acquisition of the first tire of a certain article, a recipe is created containing lighting conditions and machine configurations (described in Chapter 4). Together with the storing of the original reference image, two separated sub-images are stored independently, one containing the DOT and the second the mould code. The template matching algorithm available through the OpenCV library (Bradski and Kaehler 2008) is then used to match and locate DOT and mould codes in the new tire under assessment. In this document this algorithm will be referred as direct-TM. If a match occurs the tire is identified and, subsequently, the coordinates of the match identify the special relation between the two images (image registration). In fact, this step fulfils two required tasks: tire identification and image registration. Figure 6.3 shows an example of the offset needed for two images acquired of two different tires belonging to the same article. Figure 6.4 shows the complete images already aligned. To guarantee the quality assessment of the complete image, an extra 5% of the image is repeated at the end.

The direct-TM is versatile to image sizes and the results obtained so far demonstrated some robustness to lighting variation and shading, especially when using the normalized version of the matching function. The function systematically compares the template with every possible portion of the reference and returns a matrix of the values resulting from the matching. By defining a similarity criterion, the presence or absence of match is retrieved. If existent its coordinates are also stored.

Using direct-TM to perform tire identification and image registration was not yet validated at an industrial environment and scale but its applicability to the automatic alignment of the images was successful in all cases along this research.

Figure 6.3 - Result obtained by using direct-TM.

Figure 6.4 - Overall view of the two images to be compared.

Although not described in Chapter 4, the proposed system also comprises a color camera (AVT GC 780C). Because this camera is not directly applied to the quality inspection purpose, this was not mentioned as an integral part of the image acquisition station. The color camera function consists in capturing images of the tread that are then used for color line identification. Color line identification aims at providing redundant tire identification. There are eight different color lines. Each tire article presents a set of these color lines painted in a pre-defined order. The colors are: red, white, blue, orange, yellow, magenta, brown and green. The paints used in this process are standardized and with specific color references. Because of these specifications, the images acquired in RGB color model were converted to the cylindrical-coordinate system: HSL (hue, saturation and lightness). This step intends to facilitate the distinction between color lines (hue will vary significantly) and background removal. The tread pattern can be disregarded because of its low lightness and color clusters can be formed. By calibrating the hue, saturation and lighting intervals for each color line, the color identification of each cluster can be performed (Figure 6.5 and Figure 6.6). The color sequence identified is then compared with the expected one also included in the tire recipe. In a future industrial implementation of the proposed system, whenever the match is not successful the tire is rejected and sent to the grader.

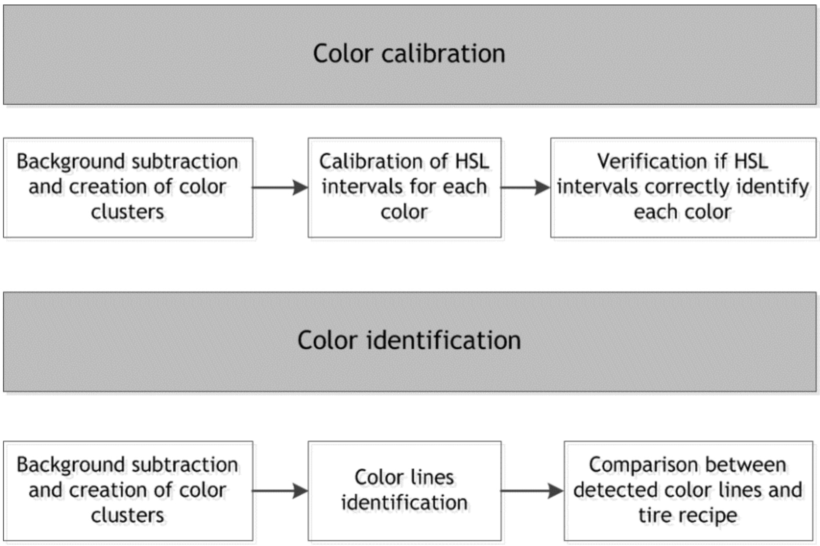


Figure 6.5 - Steps followed for color line calibration and subsequent identification.

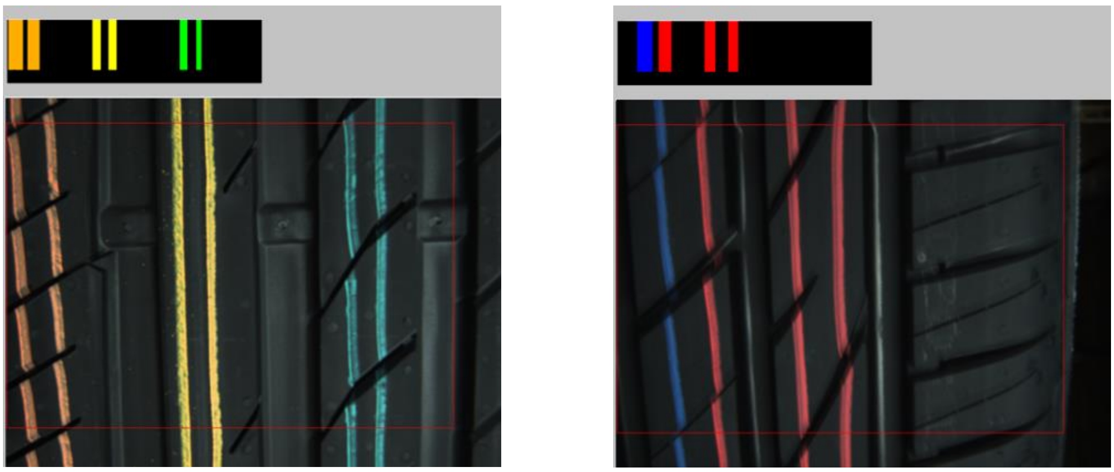


Figure 6.6 -Two images exemplifying the color lines being accurately identified. Color identification output on top and acquired images on bottom.

Validation tests were done at the Continental facilities. Because of task independency this process was not integrated in the image acquisition system. Rather this system was validated at an installation in a conveyor belt chassis. A sample of approximately 1000 tires was used to validate the color line identification. Each color was tested at least 300 times. Results show an average correct color detection of 95.7%. The color detection with lower detection rate was brown (84.6% correct detection). The specific brown in use presents a hue value close to orange and a lightness and saturation mistakable with the background. In the meanwhile Continental changed the brown color and new tests need to be done to evaluate the impact of this change in the results. Nevertheless, the detection rate is high enough to consider an implementation in which a disagreement between the colors visually identified and recipe would lead to a rejection. Tires with inverted color lines, cured in the wrong position and vulcanized in the wrong cavity can be detected by this method.

Integration and optimization of the image processing techniques and applications for tire identification is not addressed by this research. So far, the abovementioned steps towards tire identification are done off-line and by different applications. But, because they address independent tasks, the validation of each individual one is not affected by others' performance.

The techniques described for tire identification are not typically classified as pre-processing methods. Pre-processing often include filter operations which intensify or reduce certain image details. Nevertheless, in the context of this process, these steps were classified as pre-processing firstly because the image registration is essential for the subsequent steps and secondly because in the future system integration, if a certain tire is not identifiable, the quality assessment should not be performed.

6.2.2 *Strategies for automatic quality inspection*

Applying template matching techniques intends to simplify the information in the tire images and facilitate the latter classification as faulty or not. Tires contain faultless embossments, letterings and patterns that, if properly removed, would allow simpler strategies of classification. For this reason, comparing the tire under inspection to a reference model is unavoidable.

A typical template match algorithm follows the steps listed in Figure 6.7. After the image acquisition is done, the initialization of the process involves loading the image model (reference) and an image of the part to be inspected (sample). In the tire application, the fact that the acquisition step is performed separately (sidewalls, tread and inner liner) implies that an individual comparison is performed to each image area. Thus, with the current image-acquisition setup, a tire is totally assessed when four comparisons are done.

A second step before subtraction is needed. This is called image registration and takes part of pre-processing techniques. Image registration intends to find the spatial relationship between the reference and the sample to be inspected. Correctly overlaying the two images is essential in all image analysis tasks that result from a combination of images (Zitová and Flusser 2003). This can be achieved by locating and aligning special target markings (Crispin and Rankov 2009). Matching the DOT location between the two images is the mechanism used in this context. This step needs to be performed since tires are placed in the image acquisition system in a random position. This means that a certain initial feature in one image can be the last on the other.

Finally, by applying image subtraction approaches, features potentially corresponding to faults can be extracted. Usually if the difference image is a blank image it suggests that the test image is error free.

The subtraction step may be followed by morphological operations to remove any residual noise from the subtracted image and detect actual imperfections.

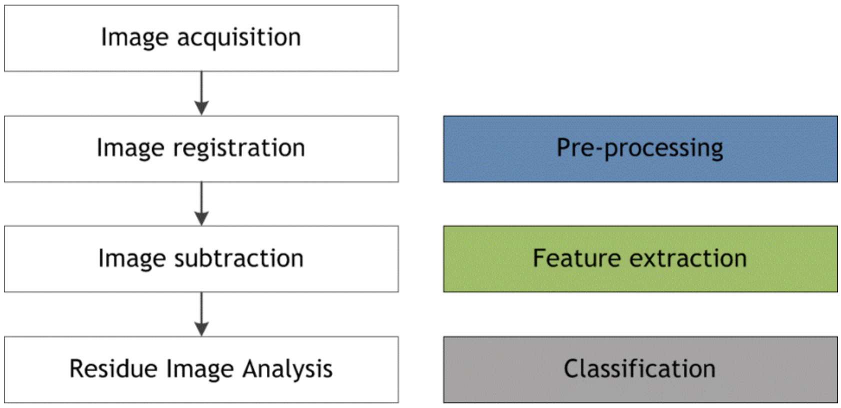


Figure 6.7 - Conventional sequence of steps in automated inspection through template matching (adapted from Crispin and Rankov (2009)).

The steps described in Figure 6.7 were implemented and tested for the tire application. The details of each step implementation will be given below. Some preliminary tests indicated that this simple and direct comparison method would not be adequate for the tire inspection application.

Figure 6.8 shows a comparison result obtained by means of the conventional TM methods. To restrict the variables and simplify the problem, this first test was done by acquiring the same tire twice. Obviously the expected outcome would be to obtain a subtraction without resulting differences. Nevertheless, Figure 6.8 shows that this is not the case. The most determinant factor contributing to this effect seems to be the low stiffness of the tire that results in surface flexibility. When physically constrained inside the image acquisition station, the tire deforms slightly and, despite the fact that same mechanical constrains are applied to a certain article, the overall image subtraction can originate artifacts depending on the tire initial input position, small speed variations, etc. This asynchronous effect is mostly visible in highly curved regions (tire shoulder displayed in Figure 6.8) where the conjugation between distortions caused by tire deformability and distortions caused by the image acquisition is highest.

The results obtained in Figure 6.8 prevent any imperfection detection to be attempted. This fact motivated the research and development of other methods that would compensate these distortions. A self-adaptive and deformable template match (SAD-TM) algorithm that dynamically adjusts the sample image according to the template is proposed (Figure 6.9). This additional step will attempt to minimize variability effects in tire's images by applying dynamic and adaptive alignment corrections with parameters that change along image width and height. This approach was not found in the literature even when looking at other applications. For this reason, custom-designed algorithms were developed. The programming language used to implement those was Pascal.

Besides the proposed step of dynamically adjusting the two images which was specifically developed in this research, some previous and subsequent steps in the process illustrated in Figure 6.9 were performed by means of available libraries. OpenGL and OpenCV were used. OpenGL was used for image texture mapping, while OpenCV was used to access to various image processing techniques.

Figure 6.8 - Sample image shown on top and the resulting differences and their classification are shown on the bottom.

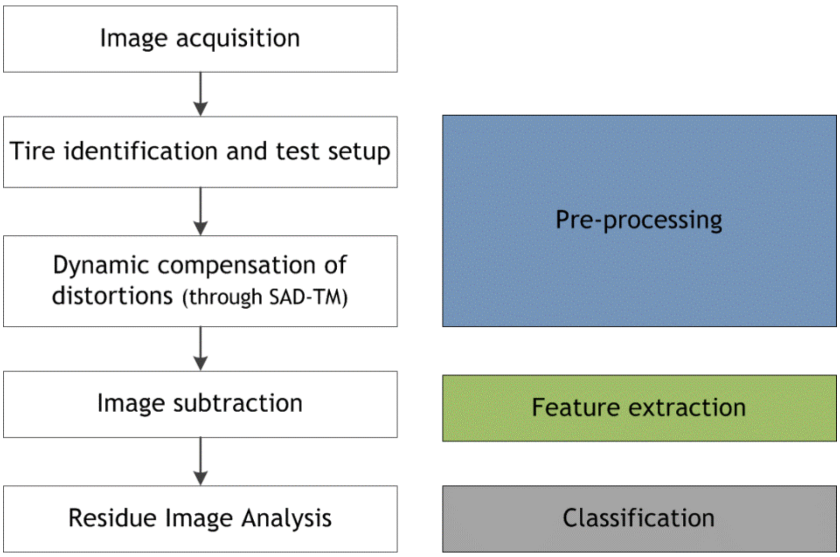


Figure 6.9 - Proposed sequence of steps for automatic imperfection detection in tires.

6.2.2.1 Comparison run setup

An application developed in the Lazarus visual programming environment will accomplish the remaining steps listed in Figure 6.9 as part of feature extraction and classification. At this stage, the program runs at an offline basis and demands user interventions. The process here described reflects the current stage of the program. Automating and optimizing various steps is possible and desirable in the future.

As stated before, the template matching technique implies that a reference image is compared to a new sample to be assessed. For this reason the first step is to configure which images to compare. The acquisitions mentioned in Chapter 4 and Chapter 5 are accessible through AutoClass database. In this database each image has an associated article, DOT, mould, etc. When configuring a template match run, the selection of images should follows the listed criteria:

- Images belonging to the same tire article;
- Images of tires cured in the same mould;
- Images of the same tire area;
- Images acquired with the same lighting conditions.

Independently of the size of the image under assessment, the comparison will be based on the dimensions of the template which is assumed to contain the whole area that needs to be analysed.

The global offset between the two images is given by the method described in previous section (direct-TM). This method provides a good approximation of the initial offset between the two images. The difficulty is that because the tire deforms, detailed image features are slightly misaligned all over the image even if the initial offset guess is perfectly accurate. This suggests that there should be another level of alignment between the two images. An alignment performed locally to smaller portions of the image is suggested. This will be called shift adjustment to distinguish from the global offset. This way the overlay between the two images is not only done globally but also accounting for a dynamic correction to each of its sub-images. This is done by permitting smaller orientations adjustments to each sub-image.

In order to implement this, three additional parameters need to be provided when setting up a comparison run: window search width (WSW), window search height (WSH), and window search radius (WSR). WSW and WSH correspond to the width and height of the sub-image, respectively. WSR refers to the number of pixels that the sub-image is allowed to navigate over the other to find the best match possible (Figure 6.10).

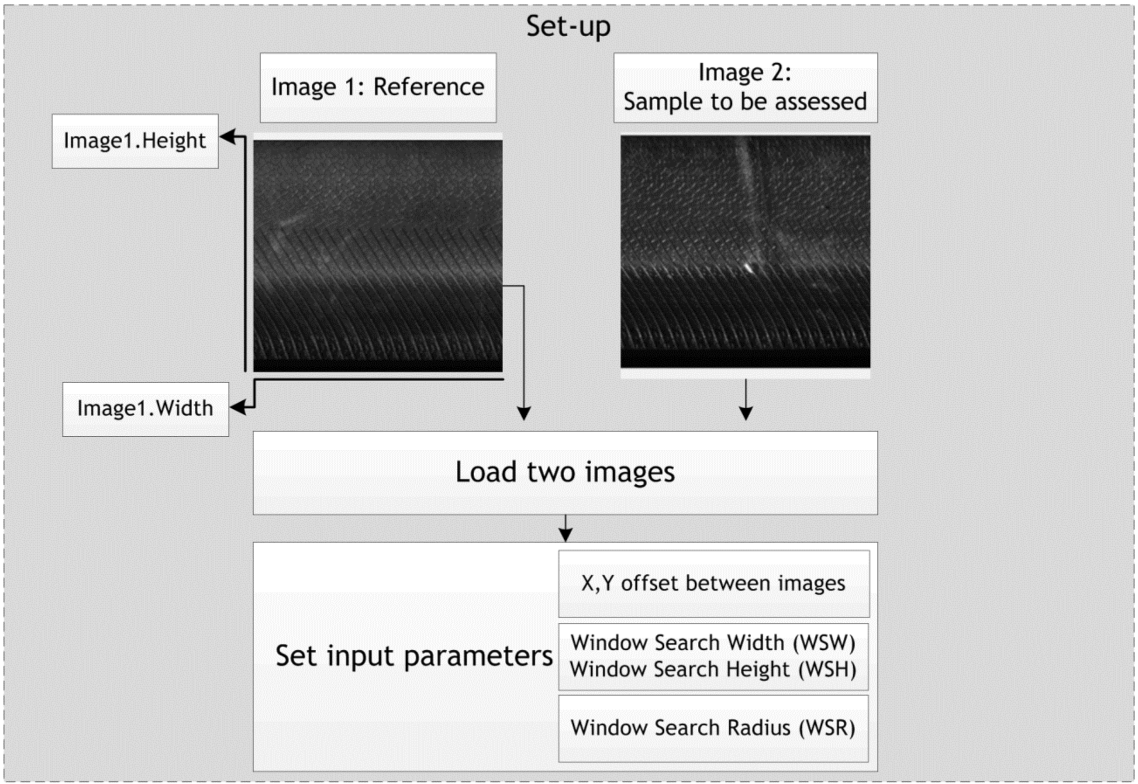


Figure 6.10 - Parameters needed to define a comparison run.

6.2.2.2 Self-adaptive and deformable template matching algorithm (SAD-TM)

The various parameters defined before will be used as inputs to the SAD-TM. The WSW and WSH define the dimensions of the sub-image. Thus the number of iterations corresponds to the number of sub-images ($\mathrm{i_0 j_0 \dots i_n j_n}$) that fit in the template global dimensions. The image should be partitioned along the two directions (width and height). Compensation along the width will mostly correct differences originated by small speed variations and tire deformations along rotation cycle. Along the height of the image, correction will be mostly needed because of image distortion along curved surfaces. In fact, the placement of the tire in the machine can create small distance variations and different physical deformations that appear as image distortions.

For each sub-image comparison, the sum of the absolute intensity (I) difference is calculated across all shifts given by the WSR. A WSR of five pixels, for example, permit that the sub-image is positioned up to a maximum of five pixels to the left, right, top or bottom. The best shift is then calculated when the sum of the absolute differences is minimum. This minimum is stored in an array that when all sub-images are analysed will contain all needed corrections. The formula used to perform these calculations is given by:

$$\min_{i_0 j_0 \dots i_n j_n} \sum_{x=0}^{WSR\times 2} \sum_{y=0}^{WSR\times 2} \left| I_{sub_{img1}} - I_{sub_{img2}} \right| \qquad 6.1$$

Figure 6.11 shows a block diagram describing the steps of the proposed algorithm. Given a template image with a certain width (Image1.Width), height (Image1.Height) and WSW and WSH assigned by the user (see section 6.2.2.1), the first step is to decompose the template image and the sample into sub-images. After that, the calculations following Equation 6.1 evolve on successive cycles as the algorithm progresses. The outcome is the shift that best aligns each of the sub-images with the reference image.

Before attempting to test this algorithm with tire images, an initial validation was done using a synthetic image in which blurred black squares were intentionally misaligned to replicate tire distortions (Figure 6.12). The template image is shown on the left part of Figure 6.12. The image on the right illustrates the shifts applied.

The top image in Figure 6.13 shows the difference between the two images when no dynamic correction is performed. After calculating the shift for each of the nine sub-images (image on the bottom left part of Figure 6.13), the sample image is reconstructed according to these values. When these corrections are applied the resulting difference is zero.

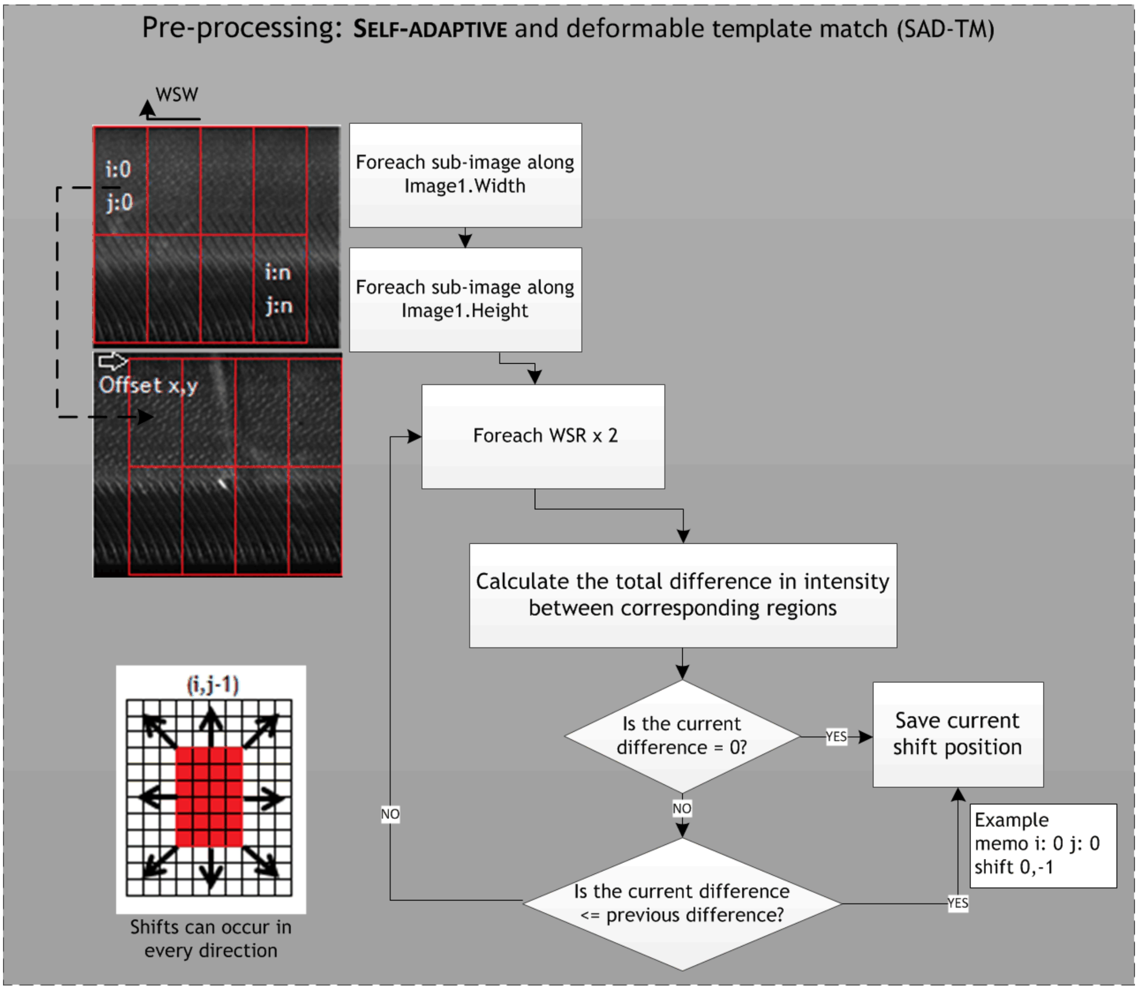


Figure 6.11 - Block diagram of the proposed algorithm.

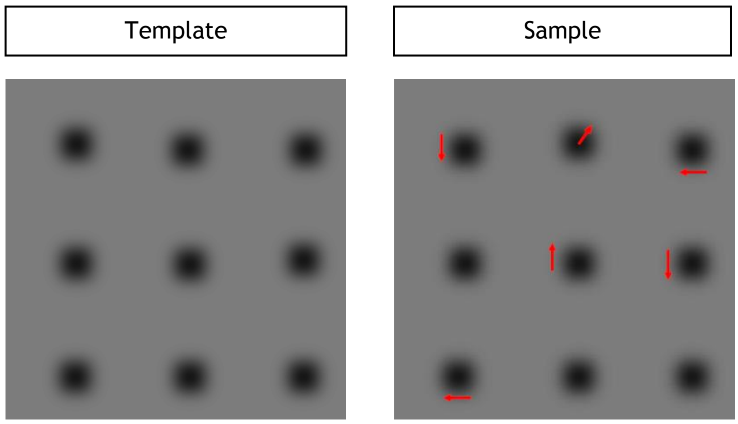


Figure 6.12 - Misalignment of blurred squares between template and sample image.

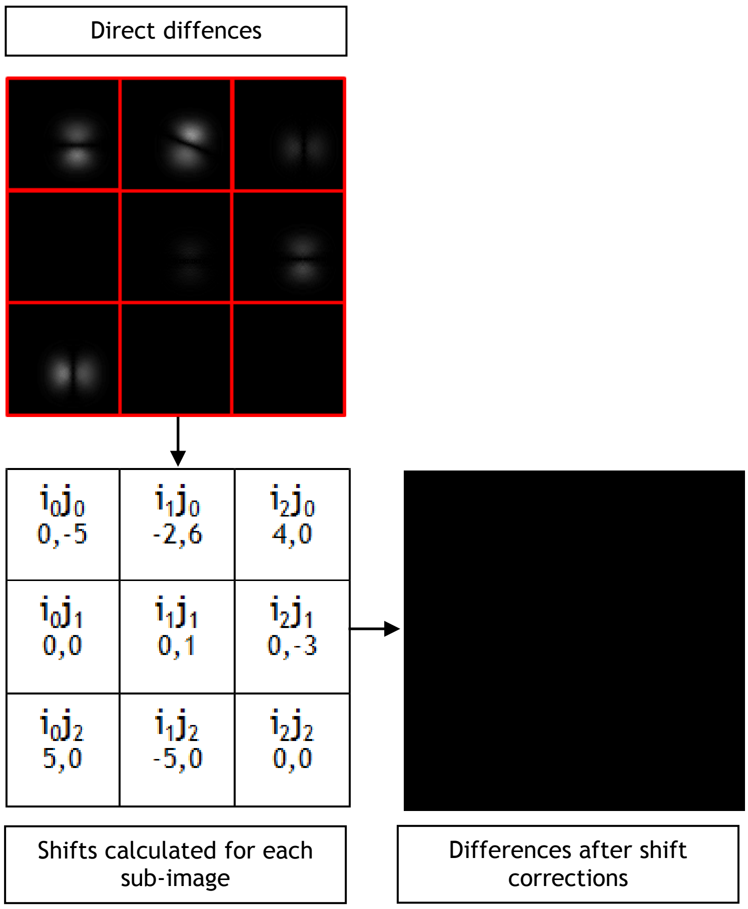


Figure 6.13 - Comparison between differences obtained before and after corrections.

Further algorithms' development occurred after the tests started to be performed with tire images. An unnoticeable effect in the synthetic images became evident by then. This refers to some discontinuities found in the reconstructed sample image in between sub-image (Figure 6.14). This was unnoticeable in the example with the synthetic image because the background was uniform.

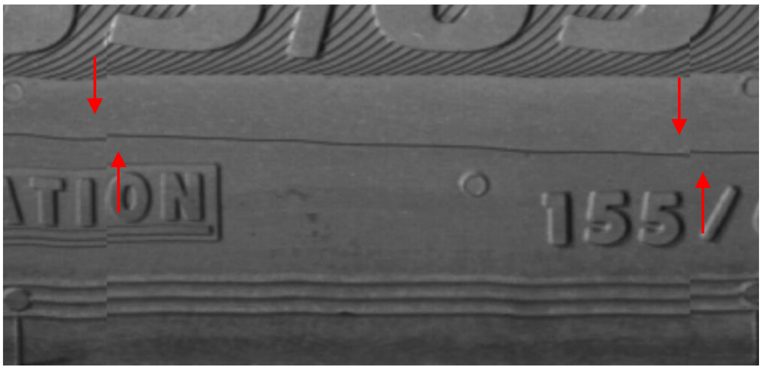


Figure 6.14 - Discontinuities visible between sub-images in the reconstructed sample image.

The effect shown in Figure 6.14 is originated when a certain sub-image is displaced in a direction that differs from the direction applied to the subsequent sub-image. Because the tire surface contains many features and patterns, these discontinuities become highly visible and can disturb the later calculation of differences. These discontinuities suggest that the optimal shift for the pixels in between the center of two consecutive sub-images should be somewhere in between the shift values, initially suggested to each sub-image. By means of a bilinear interpolation it is possible to determine the needed sub-pixel adjustment for each pixel accounting for the shifts of the neighborhood (Figure 6.15). A second bilinear interpolation will return the adequate intensity value. The interpolated value (f) is given by:

$$f(x,y) = f(0,0)(1-x)(1-y) + f(1,0)x(1-y) + f(0,1)(1-x)y + f(1,1)xy \tag{6.2}$$

where $f(0,0), f(1,0), f(0,1), f(1,1)$ are the values of the four-neighbors. The steps to perform these calculations are shown in Figure 6.15.

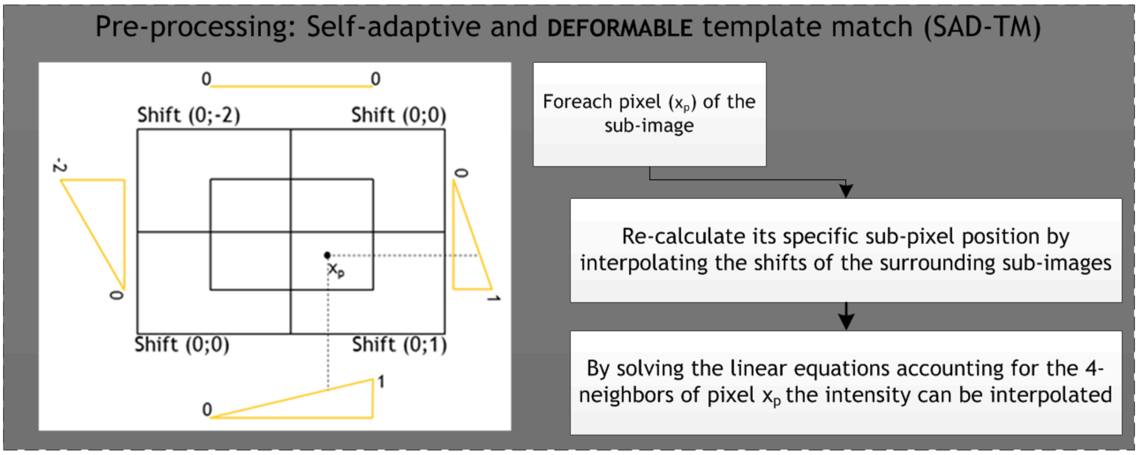


Figure 6.15 - Bilinear interpolation method used to minimize discontinuities.

Figure 6.16 shows the improved results obtained by applying corrections at the sub-pixel level by using bilinear interpolations. The discontinuities became imperceptible. This mechanism was applied with improved outcomes to all surfaces' comparisons independently of the tire area.

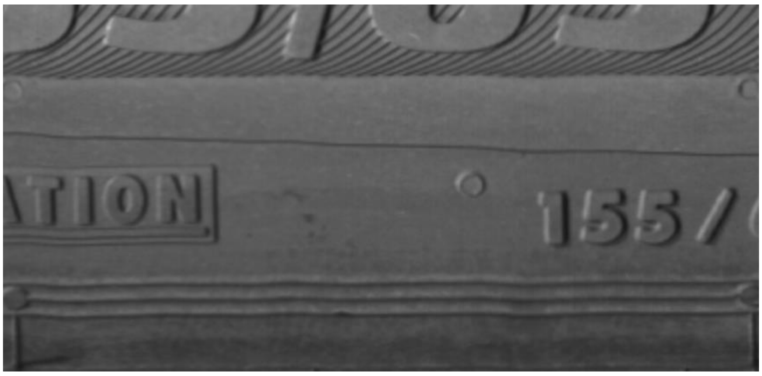


Figure 6.16 - Reconstruction of the case in Figure 6.14 after the implementation of the bilinear interpolations.

6.2.2.3 Comparison and classification

The SAD-TM is the central contribution in this automatic tire inspection program. Having the two images as accurately overlaid as possible is essential to reduce the information that is maintained when subtracting the two images. Thus after having compensated for image distortions, the subsequent step is to create an image with the same size as the template, whose intensities will be the result of subtracting the intensities between the two images following the equation:

$$I_{resultant} = G \times k \frac{|I_{template} - I_{sample}|}{k + I_{template}} \qquad 6.3$$

The resultant intensity of a certain pixel ($I_{resultant}$) is calculated by the absolute variation of intensity of that pixel in the template and in the new sample. A gain (G) value can be assigned for visualization purposes. A constant *k* is introduced so that more relevance is given to absolute variations that occur in sample image then when there are higher intensities in the template. The template corresponds to a conforming item but due to tire variability its image representation can contain brighter pixels. Differences originated because of brighter pixels in the template should be less valued than the occurrence of brighter pixels in the sample image.

The results obtained directly from this subtraction still need to be filtered to reduce noise artifacts (Figure 6.17). After that blobs with potential imperfections will be drawn and their size and location stored. OpenCV was the library used to perform these post-processing techniques.

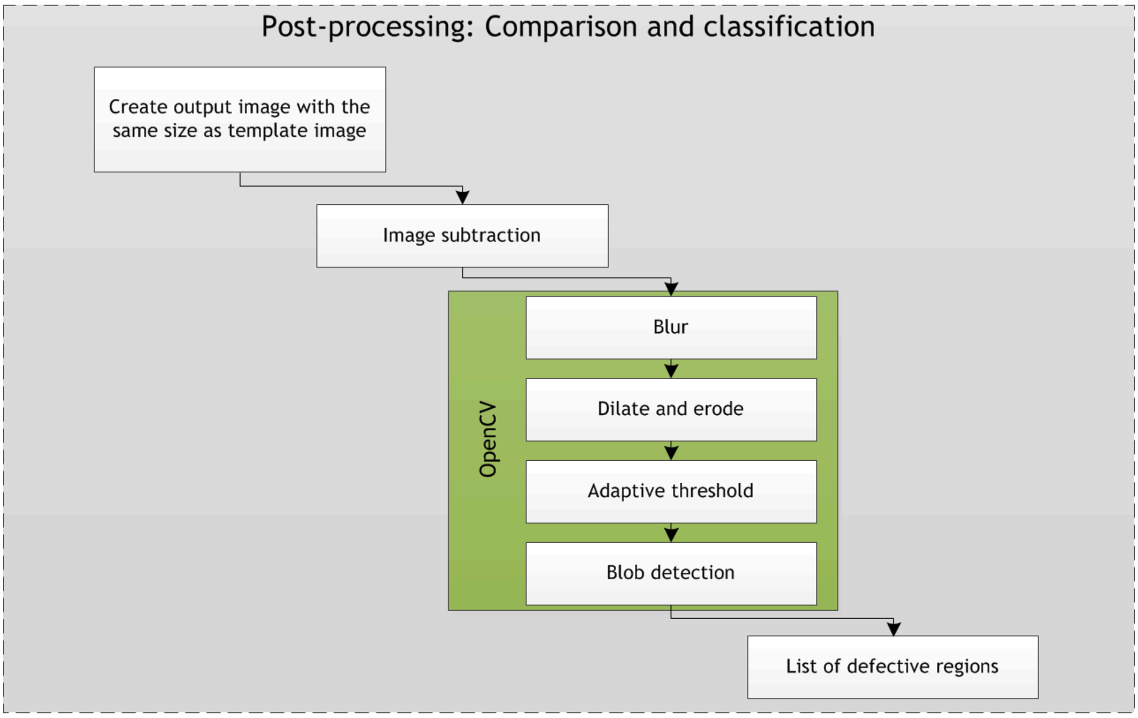


Figure 6.17 - Post-processing block diagram.

Because the output of SAD-TM is a much cleaner image than the preceding input images, the techniques required at this stage are common image processing techniques (Gonzalez and Woods 2001). The combination of techniques includes:

- Blur: intends to reduce noise by replacing each pixel by the median value in a square neighborhood.
- Dilate and Erosion are morphological operations. Dilation adds pixels to the boundaries of objects in an image, while erosion removes. When applied in sequence, dilation aims at connecting sub-components while erode operation is used to eliminate the remaining “speckle” noise.
- Adaptive threshold: used to create a binary image. Instead of applying a conventional thresholding operator that uses a global threshold for all pixels, adaptive thresholding changes the threshold dynamically over the image. This technique performed better than the conventional threshold because of the considerable lighting variations in tire application.
- Blob detection: will extract components from the binary image by their contours and calculate their centers. Close centers form one blob, which is controlled by a parameter that defines the minimum distance between blobs. This function estimates final centers of blobs and returns locations and sizes (Bradski and Kaehler 2008).

6.3 Results

The algorithms and methods described in the previous sections were applied to a set of comparison runs defined with images acquired at Continental Mabor and successfully validated by the visual inspectors at the CAI tool. Comparison runs were defined for images representing the various tires areas (sidewall, tread, inner liner). The appearance, curvature, lighting conditions and embossed patterns significantly change according to the area under analysis. This way the validation of the proposed detection methods can only be validated when tested for the three areas. While tread and inner liner typically present repetitive patterns, sidewalls are not uniformly textured. Many embossed letterings are part of the sidewalls.

Imperfections' detection was tested at the three regions. A list of 6 different NC codes (2 NC codes per region) was tested and its detection validated. Figure 6.18 shows the partial inputs and outcomes of a comparison between a conforming (template) and a non-conforming (sample) inner liner images. The sample only contains one imperfection, approximately located in the lower right corner of these images. The intermediate output shown on the bottom left represents the differences calculated by equation 6.3 after SAD-TM has been applied. On the bottom right, the blob detection results are shown. The imperfection tested in this case was a blister and its automatic detection was possible through the proposed methods. By looking at the template and sample sections, overall lighting differences are evident despite being acquired with consistent lighting conditions. Also it is important to notice that the lighting angle of incidence highlights the imperfection by creating a brighter region very favourable to the automatic detection.

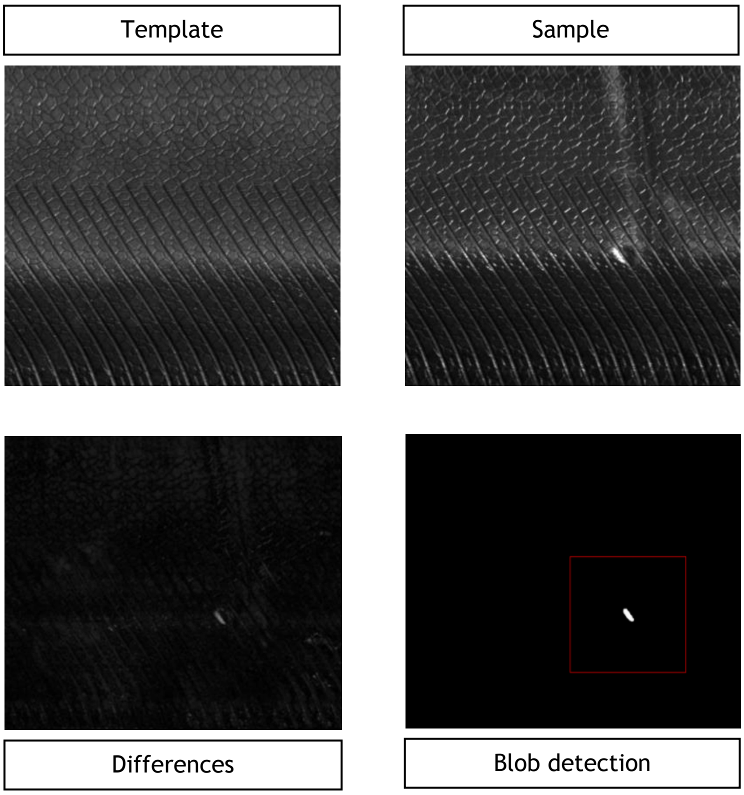


Figure 6.18 - Detection of a blister in the inner liner.

Figure 6.19 shows a zoomed out view of the comparison run demonstrated in Figure 6.18 in three different testing scenarios. The first image contains the blobs detected without the dynamic adjustment performed by SAD-TM. Many false-alarm blobs are detected specially at the high-curved region (bottom of the image), where inter tire variability is more prone to happen. In the second image the SAD-TM was applied without the bilinear interpolation. The image in the bottom is the final outcome in which SAD-TM was applied with all its capacities. A significant improvement (reduced number of false positives) was noticed by the application of adaptive shifts (second image) but only when the bilinear interpolation was performed, the results were free of false positives. The successive improvements along the three scenarios reveal the potential of the proposed SAD-TM method.

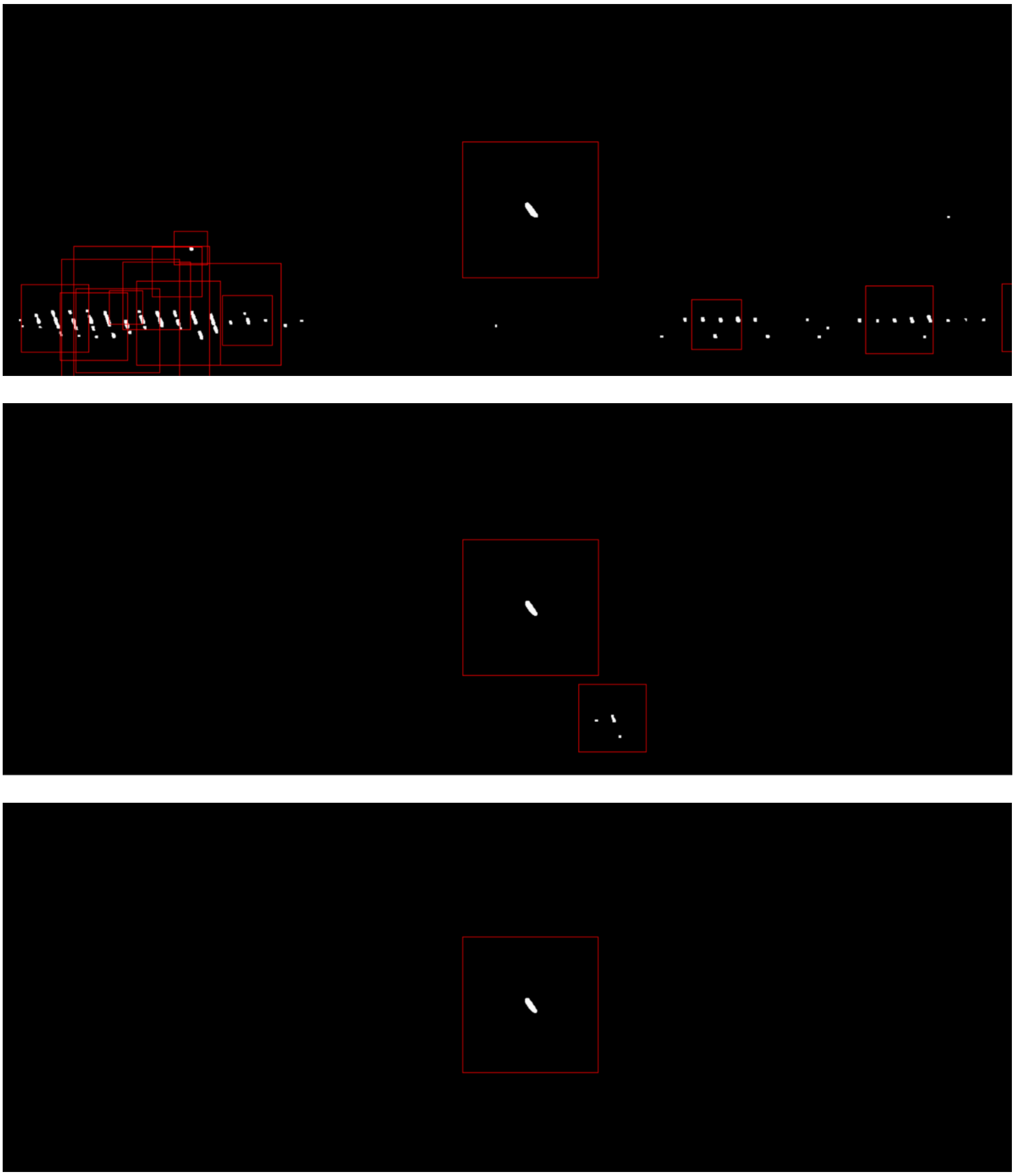


Figure 6.19 – Blobs detected for the comparison run illustrated in Figure 6.18 for three different testing scenarios and methods applied.

Figure 6.20 and Figure 6.21 show the results of comparison runs performed to the tread and sidewall regions, respectively. Likewise the previous inner liner case, the detection of imperfection was successfully done. Additionally, these three cases (Figure 6.18, Figure 6.20 and Figure 6.21) show that the detection capabilities are not restricted to imperfections with a certain shape or size. While the imperfection shown in the inner liner case presents a more rounded shape, the one for the tread is elongated and the sidewall case presents a fragmented imperfection.

The fact that the detection methods applied were able to detect the sidewall imperfection while small letterings (also create local light variations) were neglected, evidences the importance of performing accurate image subtraction.

The parameters defined for the post-processing techniques (Figure 6.17) were kept the same along comparison runs. The parameters that were adequately chosen for each case were the sub-image dimensions. They have a significant impact over the result of total differences. Understanding the relationship between sub-image size and total differences is desirable and Figure 6.22 shows a sensitivity analysis for one of the cases. The plot shows that there is an optimal zone of sub-image dimensions around 200 pixels wide. The difference tends to increase as the sub-image dimensions significantly increase or decrease. Sub-images too small may result in lack of features for a successful shift calculation while big sub-images can lead to some rigidity in the adaptation. The variation between minimum and maximum total difference reaches 20% which reveals the importance of this parameter.

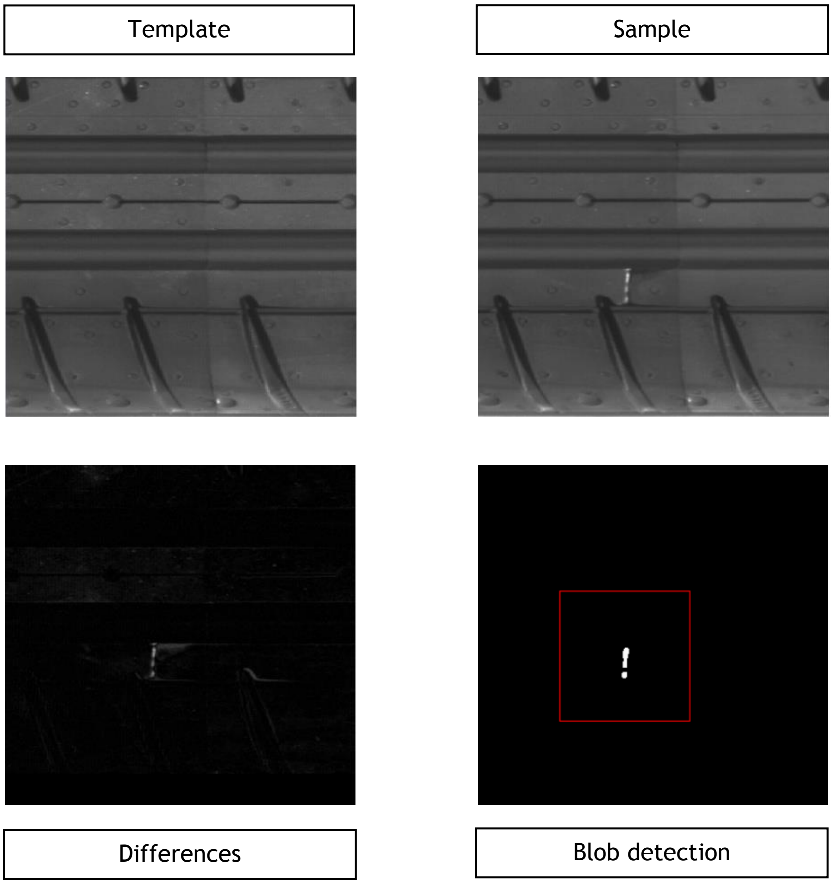


Figure 6.20 - Detection of a cut in the tread.

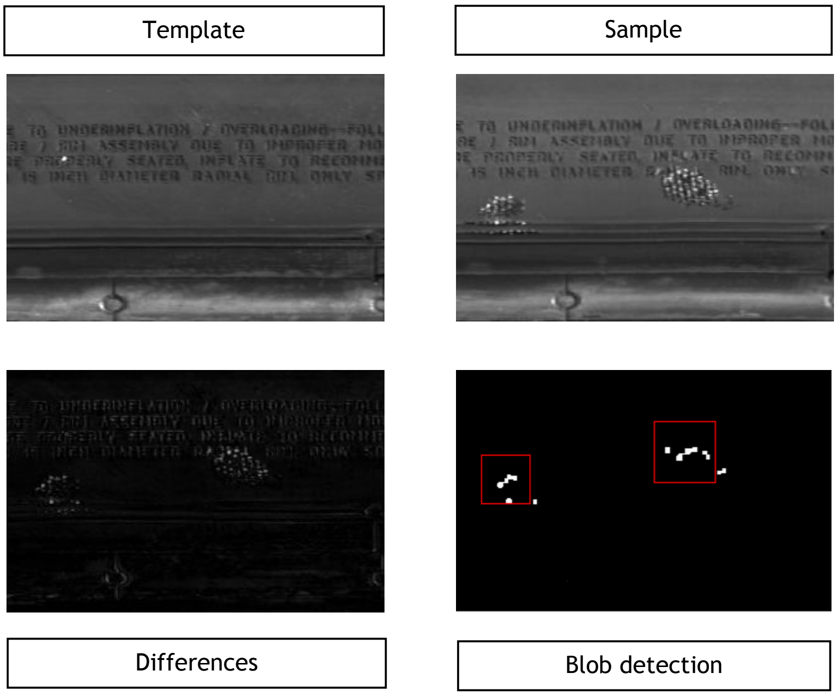


Figure 6.21 - Detection of a blemish in the sidewall.

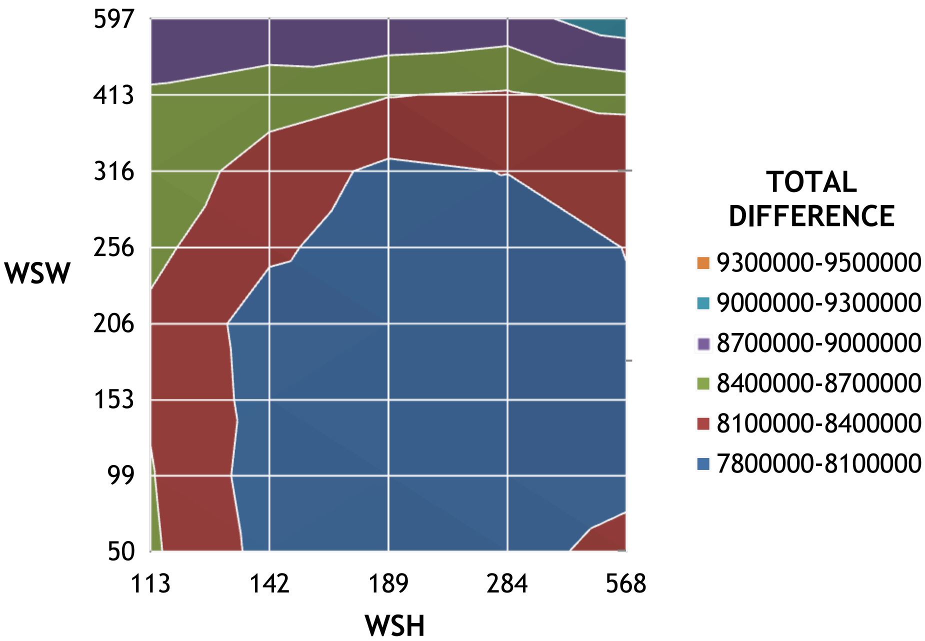


Figure 6.22 - Relation between Window Search dimensions (WSW and WSH) and the total differences obtained for each case.

The fact that the area with better results (in blue in Figure 6.22) occupies such a significantly large percentage of the area displayed shows that the algorithm is quite robust considering these parameters.

The results obtained for the comparison runs are shown in Table 6.1. Each of the 6 NC codes was tested with 3 cases. The three cases selected for each NC code varied in terms of imperfection intensity. Data from a 6-month period reveals that the 6 NC codes tested represent 29% of imperfection occurrences. All imperfections tested were correctly detected, being the smallest one 5 mm wide. The output of the automatic detection of imperfections was cross-checked and shown agreement with operators' assessments. Besides non-conforming images, also conforming images were tested (3 images per tire area).

Table 6.1 shows the percentage of the area in which blobs were detected. On average an imperfection represents an area of 2%. Thus, the reaming percentage is due to false positive blobs. At an implementation stage in which a link between automatic algorithms and CAI exists, this would be the area subjected to operators' inspection. The obtained outcomes are very promising both in the light of the CAI as well as to the targeted automatic inspection process. More tests need to be performed to better access its overall performance and robustness.

In a scenario in which the CAI exists to scrutinize the blob areas that the algorithms detect as suspicious, the present outcomes suggest that:

- the automatic detection methods could aim at filtering information rather than only highlighting - all imperfections were accurately detected and the remaining area was accurately automatically assigned as OK;
- the percentage of the area that needs to be evaluated by the operators at the CAI environment is significantly lower that the total image area (approximately 10%) – significant cost reduction can be achieved;
- while the algorithms are under development, the operators may be able to conclude that some blobs do not represent an imperfection and avoid some false positives – thus contributing to cost savings. As an example, Figure 6.23 shows a flash being automatically detected. Although it is an imperfection, this blob would be immediately ignored by the operators because they are aware of its irrelevance to customers. Nevertheless, at this stage of the development of the automatic detection techniques, the detection of flash reveals precision and is actually correct.

The results are also positive when analysing the path to achieve a fully automatic inspection. The fact that some images were assigned as conforming in agreement with operators' decisions suggests that the defined strategy is valid.

Results also reveal that future development of the algorithms should focus on reducing the percentage of false positives.

The aim of this chapter was to present the design and implement a strategy for the development of methods for the automatic tire quality inspection. The tire raises many challenges in terms of the applicability of available image processing techniques and thus motivated the development of a novel approach. For this reason the main work done was to implement and carefully analyse each step of the process.

Table 6.1 - Results obtained in the quality assessment of images from the inner liner, tread, sidewall.

Area	NC code	Blob area sent to CAI
Inner liner	50A	11.9%
		14.0%
		3.2%
	50C	10.8%
		27.0%
		2.0%
	None	0.0%
		10.0%
		4.0%

Area	NC code	Blob area sent to CAI
Tread	11	2.2%
		30.8%
		1.4%
	12A	11.3%
		7.6%
		14.8%
	None	0.0%
		0.0%
		7.0%

Area	NC code	Blob area sent to CAI
Sidewall	32B	20.5%
		24.2%
		17.0%
	33	5.8%
		12.0%
		8.4%
	None	4.4%
		3.1%
		4.5%

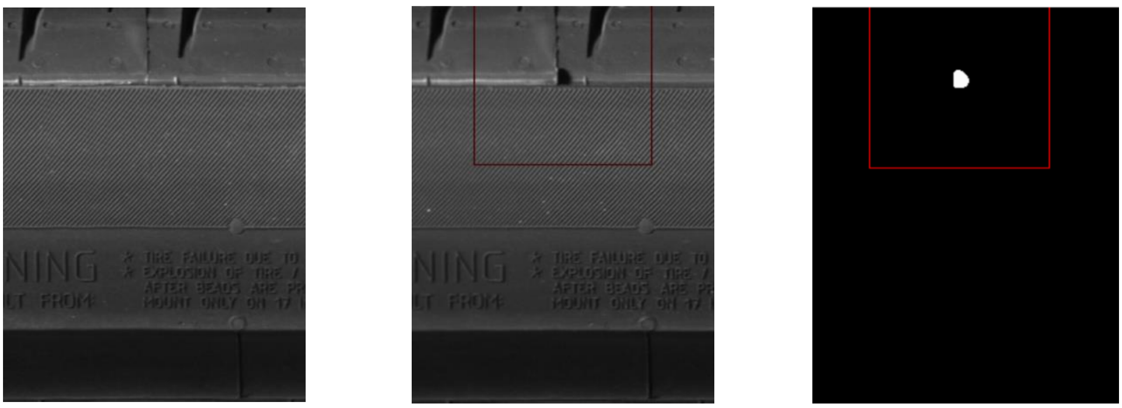


Figure 6.23 - Detection of flash in the sidewall.

6.4 References

Adelson, E.H. 2000. "Lightness Perception and Lightness Illusions." In The New Cognitive Neurosciences, 339-351. Cambridge: MIT Press.

Bozma, H. Işıl, and Hülya Yalçın. 2002. "Visual processing and classification of items on a moving conveyor: a selective perception approach." Robotics and Computer-Integrated Manufacturing no. 18 (2):125-133.

Bradski, Gary, and Adrian Kaehler. 2008. Learning OpenCV: Computer Vision with the OpenCV Library: O'Reilly.

Castellini, C., F. Francini, G. Longobardi, B. Tiribilli, and P. Sansoni. 1996. "On-line textile quality control using optical Fourier transforms." Optics and Lasers in Engineering no. 24 (1):19-32.

Chi-Ho, Chan, and G. K. H. Pang. 2000. "Fabric defect detection by Fourier analysis." Industry Applications, IEEE Transactions on no. 36 (5):1267-1276.

Crispin, A. J., and V. Rankov. 2009. "Evolutionary algorithm for PCB inspection." Int. J. Know.-Based Intell. Eng. Syst. no. 13 (3,4):91-101.

Cummings, M.L. 2004. "Automation Bias in Intelligent Time Critical Decision Support Systems." AIAA 3rd Intelligent Systems Conference.

Di Lazzaro, Paolo, Daniele Murra, and Barrie Schwortz. 2013. "Pattern recognition after image processing of low-contrast images, the case of the Shroud of Turin." Pattern Recognition no. 46 (7):1964-1970.

Ding, Lijin, A. Ardeshir Goshtasby, and Martin Satter. 2001. "Volume image registration by template matching." Image Vision Comput. no. 19 %6 (12):821-832 %&.

Enzberg, Sebastian, and Bernd Michaelis. 2012. "Surface Quality Inspection of Deformable Parts with Variable B-Spline Surfaces." In Pattern Recognition, edited by Axel Pinz, Thomas Pock, Horst Bischof and Franz Leberl, 175-184. Springer Berlin Heidelberg.

Farooq, Umer, Tim King, P. H. Gaskell, and N. Kapur. 2004. "Machine vision using image data feedback for fault detection in complex deformable webs." Transactions of the Institute of Measurement and Control no. 26 (2):119-137.

Gonzalez, R., and R. Woods. 2001. Digital Image Processing. Second ed: Pearson Education.

Kirlik, Alex. 2009. Adaptive Perspectives on HumanTechnology Interaction: Methods and Models for Cognitive Engineering and Human-Computer Interaction, Human Technology Interaction Series: Oxford University Press.

Li, Wei-Chen, and Du-Ming Tsai. 2011. "Automatic saw-mark detection in multicrystalline solar wafer images." Solar Energy Materials and Solar Cells no. 95 (8):2206-2220.

Lilienblum, T., P. Albrecht, R. Calow, and B. Michaelis. 2000. Dent detection in car bodies. Paper read at Pattern Recognition, 2000. Proceedings. 15th International Conference on, 2000.

Moganti, Madhav, Fikret Ercal, Cihan H. Dagli, and Shou Tsunekawa. 1996. "Automatic PCB Inspection Algorithms: A Survey." Computer Vision and Image Understanding no. 63 (2):287-313.

Newman, Timothy S., and Anil K. Jain. 1995a. "A Survey of Automated Visual Inspection." Computer Vision and Image Understanding no. 61 (2):231-262.

Newman, Timothy S., and Anil K. Jain. 1995b. "A system for 3D CAD-based inspection using range images." Pattern Recognition no. 28 (10):1555-1574.

Ngan, Henry Y. T., Grantham K. H. Pang, and Nelson H. C. Yung. 2011. "Automated fabric defect detection—A review." Image and Vision Computing no. 29 (7):442-458.

Nixon, Mark S., and Alberto S. Aguado. 2012a. "Chapter 5 - High-level feature extraction: fixed shape matching." In Feature Extraction & Image Processing for Computer Vision (Third edition), edited by Mark S. Nixon and Alberto S. Aguado, 217-291. Oxford: Academic Press.

Nixon, Mark S., and Alberto S. Aguado. 2012b. "Chapter 8 - Introduction to texture description, segmentation, and classification." In Feature Extraction & Image Processing for Computer Vision (Third edition), edited by Mark S. Nixon and Alberto S. Aguado, 399-434. Oxford: Academic Press.

Pernkopf, Franz, and Paul O'Leary. 2002. "Visual Inspection of Machined Metallic High-Precision Surfaces." EURASIP Journal on Advances in Signal Processing no. 2002 (7):650750.

Robinson, P., Y. Roodt, and A. Nel. 2012. Adaptive Multi-Scale Retinex algorithm for contrast enhancement of real world scenes. In Twenty-Third Annual Symposium of the Pattern Recognition Association of South Africa, edited by Alta de Waal. Pretoria, South Africa.

Sarvaiya, J. N., S. Patnaik, and S. Bombaywala. 2009. Image Registration by Template Matching Using Normalized Cross-Correlation. Paper read at Advances in Computing, Control, & Telecommunication Technologies, 2009. ACT '09. International Conference on, 28-29 Dec. 2009.

Shin-Min, Chao, Tsai Du-Ming, Tseng Yan-Hsin, and Jhang Yuan-Ruei. 2006. Defect detection in low-contrast glass substrates using anisotropic diffusion. Paper read at Pattern Recognition, 2006. ICPR 2006. 18th International Conference on, 0-0 0.

Tombari, F., S. Mattoccia, and L. Di Stefano. 2009. "Full-Search-Equivalent Pattern Matching with Incremental Dissimilarity Approximations." Pattern Analysis and Machine Intelligence, IEEE Transactions on no. 31 (1):129-141.

Tsai, Du-Ming, Chih-Chieh Chang, and Shin-Min Chao. 2010. "Micro-crack inspection in heterogeneously textured solar wafers using anisotropic diffusion." Image and Vision Computing no. 28 (3):491-501.

Tsai, Du-Ming, Ming-Chun Chen, Wei-Chen Li, and Wei-Yao Chiu. 2012. "A fast regularity measure for surface defect detection." Machine Vision and Applications no. 23 (5):869-886.

Tsai, Du-Ming, and Cheng-Huei Chiang. 2003. "Automatic band selection for wavelet reconstruction in the application of defect detection." Image and Vision Computing no. 21 (5):413-431.

Tsai, Du-Ming, and Tse-Yun Huang. 2003. "Automated surface inspection for statistical textures." Image and Vision Computing no. 21 (4):307-323.

Tsai, Du-Ming, and Cheng-Hsiang Yang. 2005. "A quantile–quantile plot based pattern matching for defect detection." Pattern Recognition Letters no. 26 (13):1948-1962.

Zheng, H., L. X. Kong, and S. Nahavandi. 2002. "Automatic inspection of metallic surface defects using genetic algorithms." Journal of Materials Processing Technology no. 125–126 (0):427-433.

Zitová, Barbara, and Jan Flusser. 2003. "Image registration methods: a survey." Image and Vision Computing no. 21 (11):977-1000.

Chapter 7
Conclusions

The tires' inspection process re-design is proposed in this dissertation, with the aim of improving its efficiency. The proposed process can be decomposed in the following three steps: image-acquisition, computer assisted inspection (CAI) and automatic quality assessment. Each of these processes was carefully conceived accounting for tire inspection particularities. The validation of each step was proposed aiming to answer the sub-research questions drawn in Chapter 1. The first research question raised was:

RQ 1.1: How should the image-acquisition station be designed to assure acquisition of unambiguous images of the object?

The image-acquisition station includes a combination of machine vision technologies and lighting systems, especially assembled to allow for an acquisition of appropriate tire images. One of the novel contributions of this research is to suggest that experienced visual inspectors are *per-se* the image acquisition validation method. A CAI system in which the operators access tire images and perform the quality assessment was implemented. Chapter 2 reveals the extensive and complex knowledge used by these visual inspectors while inspecting a tire, which is structured across the three SRK model knowledge levels. Having the operators validating the acquired images is an essential step to conclude about the suitability of the machine vision technologies and lighting conditions. The results shown in Chapter 4 revealed that the images provide an appropriate representation of the tire and its imperfections. This was concluded by testing a sample of 300 non-conforming tires which were correctly assessed by the visual inspectors in 97% of the cases. The change of environment from a physical manual inspection to CAI does not seem to have significantly affected the capabilities of the operators in identifying imperfect regions.

Not only validation purposes motivated the development of the CAI system. Providing operators better and uniform conditions to visualize the entire tire was also made possible with this approach. Furthermore, the elimination of physical and repetitive tasks (that make the inspection process more error prone), can create an inspection environment that favors higher efficiency and effectiveness levels. Considering a scenario in which the operators perform inspection digitally motivated the second research question:

RQ 1.2: Can the human operators perform the task with a comparable level of quality by means of the computer assisted inspection tool?

The process to obtain an answer to this question involved comparing results from an experimental design study in which a sample of tires was assessed by two groups of operators. One performed the manual inspection (control group) while the second assessed the same tire digitally (experimental group). Some differences between the two groups were noticeable, indicating that the manual process leads to slightly better outcomes. Nevertheless the difference does not seem to reflect permanent lower detection capabilities through CAI system but rather the need to account for a longer learning period, in which some of the methods used by operators need to be adjusted. More interesting results were obtained when simulating the impact of automatic quality assessment methods. The hypothesis raised was that the operators' performance would improve (in quality and quantity) if there was the possibility of reducing the information that is subjected to human assessment. In fact, when the information passed to the operators in the CAI system is restricted to automatically identified potentially defective areas, the operators' performance surpassed the current manual process, thus leading to cost savings. This suggests that automatic detection algorithms are an essential mechanism to potentiate the benefits of CAI while CAI itself is an essential source of operators' decision criteria. These criteria are not always standardizable and CAI has the potential of harvesting information that will later be used in the continuous development of automatic algorithms.

Intrinsic tire characteristics create many challenges in both the development of the image acquisition system and in the definition of image processing techniques for imperfection detection. Its rounded shape, curved surfaces, variable surface appearance and deformable material, places tire application as one of the most challenging products to be inspected automatically. As a result, the third research question is:

RQ 1.3: Which image processing techniques are adequate to assist in the detection of non-conformities?

Innovative algorithms were proposed in this dissertation and proved to be successful in the imperfection detection. Compensating tire deformability by applying dynamic shift corrections by means of the SAD-TM method generated promising outcomes, not achievable with simplistic image processing techniques. The algorithms demonstrated capabilities to accurately reduce the amount of information shown to operators in CAI (up to 90%). Nevertheless, false positive cases motivate the existence of a subsequent step of human validation of the automatic decision. These dependencies and collaboration between the two processes (CAI and automatic inspection) favors the overall inspection result. A continuous development of automatic methods by learning from human based decision can, in the future, lead to a fully automatic inspection process. Nevertheless, more developments and tests need to be performed. A fully automatic solution can only be guaranteed once all imperfection codes are tested and passible of being identified.

The strategy of making operators and their know-how part of an improved quality inspection process poses as one of the main contributions of this dissertation. In a context in which most literature suggests automated solutions only restrained by technological or budget constraints, this methodology presents very distinctive characteristics. But these characteristics should, in no way, be considered as less advantageous. They make this process capable of answering to requirements posed by a very specific industry. Tires are critical safety components; the manufacturing plants produce simultaneously a large number of different articles; the production process is long and composed of many steps; the main raw material is quite prone to surface defects, leads to a deformable part, and provides poor surface contrast and; the large amount of geometrical features leads to the existence of a high variety of distinct NCs that can be present in any place of the tire. This makes the application studied in this dissertation a very demanding one. The fact that the proposed inspection solution managed to get very positive and promising results, shows that it can be applied to other industries that might be currently facing difficulties in sustaining manual inspection process (due to costs) and in implementing fully automated quality inspection processes. The difficulties most frequently mentioned in transferring the quality control to a fully automated system arise from limitations in incorporating the equivalent human-based quality standards. If this step is not carefully accounted for, the resulting quality assessment may reveal lower flexibility and/or performance. The strategy proposed in this dissertation provides new thoughts and perspectives over this problem.

7.1 Recommendations for continuous development

The results described along this dissertation, aiming at addressing the main research question, suggest that the benefits initially envisaged with the proposed quality system re-design can be achievable. Even though, entering a stage of industrial implementation imposes new requirements not yet tested. For this reason, the next stage of this project should still be mostly focused on further development implementation and in enlarging the scale of the tests.

The solutions developed so far were more tailored to the concept validation phase with low attention given to integration and more focus in testing flexibility. Thus, each of the main sub-components of the system (image acquisition, CAI and automatic quality assessment) was tested offline and individually. This disconnected prototype enabled a higher control and analyses over each sub-component but limited the number of cases tested and the applicability of feedback loops. As an example, offline mode created difficulties in the definition of adjustments in image acquisition conditions upon CAI and automatic decisions failures. Sometimes days or even weeks separated the acquisition moment from the subsequent steps which compromised the possibilities of redefining image acquisition conditions for the same tire. Also, the impact of algorithms in filtering information to operators was only simulated and not tested with real automatic outputs. If this prototyping scenario was satisfactory so far, the leverage of testing cases and continuous system development requires an online and integrated testing platform. The last research question is related with this aspect:

RQ 1.4: How should the design and the implementation methodology be so that a continuous increase in the system Level of Automation is possible?

The interdependencies defined between image acquisition, operators' CAI and automatic detection methods and, the collaborative quality assessment provided by the last two, are the aspects of this system that will mostly contribute to higher process efficiencies. But fully understanding these benefits is only possible with a first online implementation. Figure 7.1 contains a suggestion for the next prototyping scenario. In this scenario, the image acquisition station would be immediately followed by two quality decision processes. Two operators (or one performing both steps) would need to be assigned to this prototyping cell. One would be allocated to CAI and receives the images, while the second would perform the current manual process and thus receives the tire. The automatic algorithms would be applied to the acquired images and only potential defective regions would be shown to the operator. After concluding the inspection, each decision would be stored in the local information system. The control loop would start if the two decisions do not match. In this case, the operators would be informed and inconsistency cause would be investigated. The outcomes of this can motivate improvements in the previous sub-systems. One scenario could be when the operator at the CAI system misses one imperfection. In this case, the failure could be associated to individual distractions, or system-related aspects. In the last scenario, the error would be caused by the automatic detection methods if the image contains the imperfection or by the image acquisition setup if the imperfection is not visible at all. The tracking of these failures and its storage will contribute to a continuous and iterative system development essential to create foundations to an industrial implementation.

7.2 Future work

From the concept generation phase until the moment a prototype was installed at Continental Mabor facilities, many aspects and technological solutions implicitly required in this system were specified and implemented. The complexity and diversity of systems and sub-systems required the understanding of many knowledge domains. To assess the overall impact of this novel inspection concept, each individual system needed to be implemented and validated. Now that the first results positively validated the proposed inspection system, a stage of optimization and improvements can be proposed. Each sub-component of the system should be carefully analyzed and its improvements prioritized.

Regarding the image acquisition system, future work should concentrate on:

- Finding an alternative to the current lighting adjustment system (articulated arms composed by servos). This can be done by considering linear actuators or a more radical change, by organizing tires in batches and have machines with different lighting configurations .
- Improvements in the acquisition of the bead edge region by possibly considering 3d laser scans. This region is always supposed to be as flat and smooth as possible and, thus, any height variation is caused by non-conformities. The unambiguous rejection criterion makes it appropriate to be automatically detected.
- Analyze alternative lighting systems for the inner liner.

The future work related with automatic quality assessment methods should include:

- Testing other classification methods such as neural network or support vector machine to distinguish between false positive blobs and defective blobs.
- Enlarging the number of NC codes tested.
- Integrate the various applications and automate some steps in order to make the process of comparison runs quicker.
- Design a training program to fully acquaint operators with CAI. This might allow the reduction of inspection time, incorrect decisions and, as a consequence of these factors, cost.

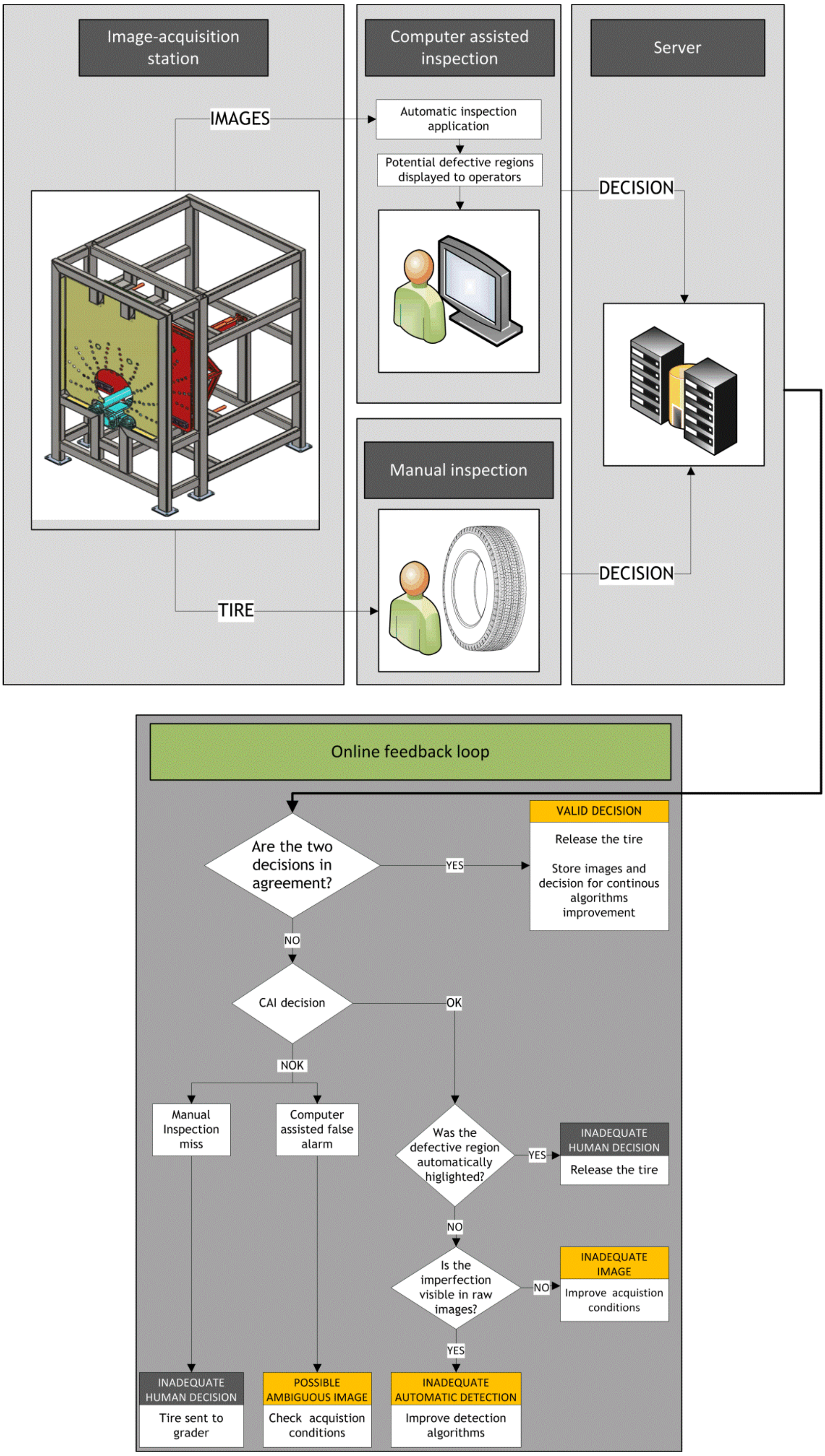


Figure 7.1 - Proposed methodology for continuous system development.