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Contextual Knowledge to Enhance Workplace Hazard Recognition and Interpretation in a Cognitive Vision Platform

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Abstract

The combination of vision and sensor data together with the resulting necessity for formal representations builds a central component of an autonomous Cyber Physical System for detection and tracking of laborers in workplaces environments. This system must be adaptable and perceive the environment as automatically as possible, performing in a variety of plants and scenes without the necessity of recoding the application for each specific use. But each recognition system has its own inherent limits, especially those which task is to work in unidentified environments and deal with unknown scenarios and specifications. The platform described in this paper takes this into account by connecting the probabilistic area of event detection with the logical area of formal reasoning in a Cognitive Vision Platform for Hazard Control (CVP-HC). In order to support formal reasoning, additional relational scene information is supplied to the recognition system. In this platform, the contextual knowledge is used to improve the recognition and interpretation of detected events. This relational data together with all collected information is represented explicitly as a Set of Experience Knowledge Structure (SOEKS), categorized and stored as a Decisional DNA (DDNA), a decisional safety fingerprint of a company. By these means, the systems assesses and addresses critical unsafe behaviors whilst gives support to an explicit long term culture change process. By the use of context the CVP-HC is capable adjust accordingly without the need of rewriting the application's code every time conditions or specifications changes.

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1. Introduction

Hazard control is essential to ensure the occupational health and safety of workers[1]. In this context, monitoring of workers activities and identifying any risk present in the workplace emerged as a need.

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The use of sensors data and computer vision techniques support the fast and automated monitoring for detection of potentially dangerous situations. This information can be used to predict any incident, to provide feedback and manage workers behavior to perform the work in a safe manner[2]. However, even with the advances in computer vision techniques, the accuracy of current visual sensing facilities when operating in real life scenarios, subject to change in illumination, variation in backgrounds, and different camera resolutions, still remains a challenge[3]. These technologies lack adaptability to the broad industrial environments and existing situations. As a result, the existing systems create case-based applications that work only for specific circumstances and any change in conditions would result in rewriting most of the application code.

One of the most recent trends to overcome the limitation of computer vision systems is the coupling of cognition and vision into cognitive computer vision. Cognitive computer vision involves functionalities such as knowledge formalism, learning, recognition and categorization, reasoning about events for decision making, and goal specification, all of which are concerned with the semantics of the relationship between visual agents and their environment i.e. context. The visual information in combination with explicit symbolic models of context, can engage the system in purposive goal-directed behavior, adjusting to unforeseen changes of the visual environment, and anticipating the occurrence of events[4].

For instance, an automatic semantic and flexible annotation service able to work in a variety of video analysis with little modification to the code using Set of Experience Knowledge Structure (SOEKS) was proposed in Zambrano et al. work[5]. This system is a pathway towards cognitive vision and it is composed, basically, by the combinations of detection algorithms and an experience based approximation based on the Set of Experience Knowledge Structure (SOEKS). Results have shown enhancements in scalability, but the tool was designed for off-line video analysis and does not have the capability of working in real time implementation.

In the present approach we extend the idea of Zambrano et al. to a real time Cyber Physical System (CPS) for hazard control in industrial environments. Aiming at assisting the safety management process, especially in industrial environments we propose a Cognitive Platform for Hazard Control (CVP-HC). This CPS perceives critical safety behaviors in real time giving support for the behavior-based safety strategy whilst stores information in a structured way for latter access and to support an explicit long term culture change process that can be systematically assessed and shared. The CVP-HC is a scalable yet adaptable system capable of working in a variety of video analysis scenarios attending specific safety requirements of different industries by modifying its behavior accordingly. The proposed system is based on the Set of Experience Knowledge Structure (SOEKS or SOE in short) and Decisional DNA (DDNA), which were first presented by Sanin and Szczerbicki[6-9] and later enhanced further for a number of dedicated domains[10, 11]. In order to support formal reasoning, additional relational scene information is sensed or provided to the recognition system through different sources of information. In this paper we highlight how this contextual knowledge can be used to characterize and improve the recognition and interpretation of detected events.

This paper is organized as follows: In Section 2, workplace safety management practices are presented with special focus to two main approaches: the behavior-based and culture change. In Section 3 the proposed Cognitive Vision Platform for Hazard Control (CVP-HC) to support the integration of both methods is introduced. In section the importance of context to enhance the recognition and interpretation of dangerous situations are shown. In addition, it is also presented in Section 4 how this context is modeled and represented as in the Set of Experience knowledge Structure (SOEKS) which are grouped and stored as a Decisional DNA (DDNA) for later access and sharing. Finally, in Section 5 conclusions and future work are given.

2. Managing Workplace Safety

Managing safety is the best way to prevent injuries in workplace[12]. In industrial environments, workers are exposed to risks in a variety of unsafe situations, such as when accessing controlled zones without authorization, crossing yellow lines, not respecting safe distances from machines and areas, not wearing the required personal protective equipment (PPE), on track of moving machines or falling objects among others. There are basically two prominent and seemingly antagonistic safety management approaches: the behavior-based and culture change[13]. Behavior-based safety management is essentially a “bottom-up” approach. The focus of attention is directed at specific safety-related behaviors that are usually performed by frontline employees, for instance, workers on an

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assembly line in a factory[14]. It is also an analytic or data-driven rubric, which means that critical behaviors are objectively identified and targeted for change. The objective goal is usually set to focus activity, and feedback is provided to measure performance, provide support, and foster continuous progress[13]. The behavior-based approaches are essentially setting specific which implies that identification of specific behaviors in a specific environment is central to this methodology. Behavior-based safety management experts claim that the overall approach is broadly applicable to different work environments, but each application needs to be specific and tailored to the setting in question[13]. For this reason, building a system capable of support behavior-based safety management of a variety of scenarios subject to their own settings at the same time as being specific and meaningful still remains a challenge.

Furthermore, behavior-based safety are intended to be short-term or one shot efforts, which means it might not be sufficient to provide a long term change in perception of unsafe behaviors and must be a continuous effort[15]. For example, a behavior-based program may show that a positive reinforcement increases the usage of a specify PPE (for instance, protective hard hat at construction sites). However, when this reinforcement is no longer provided, the use of this equipment should gradually go back to baseline levels[16].

On the other hand, culture change methodologies to safety come mostly from management and organizational behavior theory and are more "top down"[13]. As well as groups of people, organizations also have cultures which can be characterized, for instance, as weak or strong, rigid or flexible, functional or dysfunctional, and which influence their employees[17]. The logic of the culture change approach is that the organization's basic values or conventions about safety largely impact the level of effort and initiatives used by that organization to manage safety. As a consequence, these activities are used to guide and influence the perceptions of employees about the importance of safety and their expectations in relation to safe work practices, hazard control and incident reporting[13].

For the culture change approach, the focus is understanding and often modifying the central values and beliefs of the organization. Therefore, to make significant and lasting improvements in safety, the culture of the organization needs to be understood and changed. Organizations often share common practices and experience similar events in regards to safety. Yet, companies may share certain cultural values. However, the culture of each organization is thought to be unique and the safety behavior of their members and how it is approached must be understood in its own context[13]. It is important to point out that an organization culture can be resistant to change, leading to an exhausting and slow process. For this reason, a system that gives management support for this methodology must safely store information that can be easily accessed to delineate the culture change process in terms of stages and used to measure progress and impact of programs and practices.

Finally, the behavior-based and culture change methodologies can be considered complementary to the extent that their respective strengths can be combined. By combining these two approaches into one unique platform, the objective and empirical analysis of critical safety-related behaviors strategy can be integrated with an organizational culture changing process. It results in a more comprehensive and potentially effective methodology to manage workplaces safety[18].

3. Cognitive Vision Platform for Hazard Control (CVP-HC)

Aiming at assisting the safety management process especially in industrial environments a Cognitive Vision Platform for Hazard Control (CVP-HC) is proposed. The CVP-HC is a Cyber Physical System that gives support for the behavior-based safety strategy whilst stores structured information for later assessment, analysis and sharing, which can be used to assist a long term culture change process in the company. In addition, our platform aims to attend the fundamental property of cognitive vision systems: the extendability[19]. This implies that we propose to deal with more situations than exactly those which the platform has been foreseen and tested for it during the design and programming process. By this means, the system is designed to adapt to different scenarios and applications and at the same time being specific and meaningful.

In this platform the critical safety-related behaviors are represented as rules and detected events are characterized by five main attributes:

- Workers
- Personal Protective Equipment (PPE)
- Potentially Dangerous Object, Machinery or Area (PDOMA)

- Action/State
- Context

Workers, PPE and PDOMA are detected through a Convolutional Neural Network and represented as variables in our system. Action/State are represented as functions that model the relationship among those variables. Unsafe events occur when the Action/States violates one of the given rules and are represented as a probabilistic value. The Table 1 presents few examples of PPE, PDOMA and Action/State attributes. To support formal reasoning Context is evoked when an event occurs and can modify the state of the event or influence its interpretation.

Table 1. Examples of PPE, PDOMA and Action/State attributes.

PPE	PDOMA	Action/State
Boots	Falling objects	Walking
Ear plugs	Cars	Running
Face masks	Ladder	Falling
Gloves	Machines	Laying
Goggles	Robots	Integrating
Hard hats	Restricted areas	Standing
High visibility clothing	Yellow lines	Wearing
Respirators	Dunnage	Climbing
Safety harnesses	Wiring	Lifting

The Platform functioning is composed, basically by four layers: System Configuration, Central Reasoning, Experiences Validation, and System Monitoring, which will be described as follow:

- **System Configuration:** This layer comprehends the selection of the attributes according to industry requirements; labelling of machinery, areas and plants of the workplace being captured by the camera and sensors; creation of the rules according to the safety requirements and configuration of other functionalities such as frame and learning rate.
- **Central Reasoning:** The Central Reasoning layer is the intelligence of the entire system. It is composed by a Convolutional Neural Network arranged in a hierarchical structure to support detection of attributes, location and recognition of events, interpretation of the role (enhanced by the use of context) to determine the level of risk present in the recognized entity.
- **Experiences Validation:** In this layer, the collected experiences structure are checked and a group is selected. According to the learning rate given on the System Configuration, the user is queried to check if the given solution for a SOE is reasonable. Once accepted by the user as a correct solution, the SOE is stored in the decisional DNA repository. The stored experiences are used to calibrate the system and improve its specify when retrained from time to time. It ensures that the decision making provided by the CVP-HC is perfectly adjusted to the organization's safety DNA.
- **Monitoring:** This layer represents the monitoring of workers' activities. When a hazard is identified by the system an alert message is shown on the application interface with details/recommendations about the existing risk.

4. Context to Enhance Workplace Hazard Recognition and Interpretation

The context in our platform is composed by additional relational knowledge information which can be sensed or provided to the reasoning system through different sources (sensors, input signals, user preferences, computer data, past experiences, extra visual information, etc.) and explicitly represented, as shown in Fig. 1. All the information that cannot be proceduralized is treated as external information and not accounted for reasoning.

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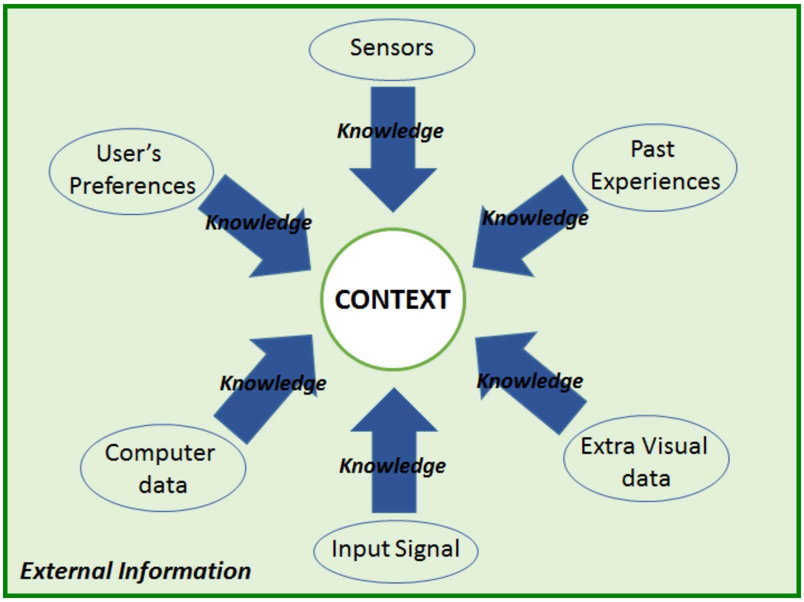

Fig. 1. Different sources of Contextual Knowledge.

This contextual knowledge is used for two main purposes:

- **Improve certainty and accuracy of events**
- **Improve interpretation of events**

Context can disambiguate low quality inputs in recognition tasks improving accuracy[20]. We also connect our thoughts to Laplace's view that the world is deterministic and we can increase the certainty of a probabilistic event if sufficient information is available[21]. The interpretation of an event and its implications is indispensable for a decision making process, especially in situations that require quick and accurate response due to the severity of their implications.

In our platform we define safety context of a workplace as the set of all the contextual knowledge that can be explicitly represented to characterize the situation in which the event occurs. Context plays an important role in many domains, especially for activities such as foreseeing context changes and can be mobilized to understand a given situated problem, explaining unanticipated events, helping to handle them, or aiding to focus attention[22].

4.1 Context for modifying system behavior

Many workplace hazards are context related. Context may influences the causality of events, i.e. unsafe events may occur with more or less frequency because of contextual settings. In addition, the interpretation of a detected event and also the level of risk it presents may also change according to contextual factors. Some common contextual elements connected to safety behaviors and that can possibly affect their causation and interpretation are presented in Table 2.

The way how contextual knowledge influences events causation and interpretation depends on the nature of its characteristics and also past observations, which we call experiences. Experiences are added during design process (mostly common sense knowledge or available), gathered as the system runs or given as input entry (which can come from the user past observations, from result of accredited research; technical knowledge etc.).

For example, Folkard, Lombardi, and Tucker show in their research that shift workers are more likely to be injured or involved in an incident at work because of the kind of activity they usually perform and the general conditions under which they work. For instance in Australia, the work-related injury rate of shift workers was found

113 per 1,000 employed people, which is almost twice the rate of those who worked regular day time hours (60 per 1,000 employed people)[23]. This information can be feed into the system to increase the certainty of a detected situation or change the state of an uncertain event where the monitored worker is a shift worker or at last bring it to notice[24].

Table 2. Contextual elements connected to safety behaviors and that can affect their causation and interpretation.

Contextual Element	Examples
Worker profile	shift worker, function, age, experience
Day of the week	workday, weekend
Shift	morning, afternoon, night
Season	summer, spring, autumn, winter
Industry Type	construction, IT, manufacturing
Location of Industry	country, city, area
Industry size	small, medium, large
Time since last safety training	in months, days, weeks
Machine or object status	in operation, paused, switched off, in movement, falling
Computer data	date, time
Other sensor data	level of oxygen, temperature, air contamination, fire alarm, lightening
Extra visual information	worker identity, presence of other objects etc.

The day of the week was also reported to have influence in injuries caused in workplaces. United States Bureau of Labor Statistics (BLS) estimated that in that 2004 Sundays had the highest rate overall – 40% higher than the average rate. Saturdays had the next greatest rate. Among the explanations for this trend are: higher alcohol/drug consumption, second jobs and less supervision available. Lower volunteer staff for patient handling was a complication for events occurring on the weekend according to this study[25].

A number of authors have observed that many of the headlines workplace catastrophes of the past few decades, such as Chernobyl, Bhopal, Exxon Valdez, Three Mile Island, and the Estonia ferry, have all happened in the very early hours of the morning. Furthermore, investigations of these disasters have concluded that they were, at least to some extent, due to fatigue leading to human error[24]. In addition, injury accident records collected during 38 years by the safety services in a steel plant in Cracow, Poland has shown that on the night shift, the accident rate was lower during and immediately after the meal breaks (from 02:00 to 04:00), which is when the workers usually try to slow the tempo of work. Subsequently, a distinct rise on accidents was observed in the last hours of the shift (which is when workers generally speed to get tasks accomplished on time). Still according to the study in Cracow, commonly, the number of accidents was significantly greater in summer than in winter[26].

Studies have also shown discrepancies among industries from different types and locations. A report characterizing work-related fatal injuries occurring in Louisiana from 2015 through 2016 and captured from a multisource work-related fatality surveillance system developed by the Louisiana Department of Health has shown that oil and gas extraction, agriculture and transportation together account for 63% of all fatalities on that period. Yet, each industry has rates consistently greater than the US rates, except for Oil and Gas extraction, which has greater variation in rates. The authors highlight multiple factors that may influence a state's occupational injury rate, including the state's industry profile, workplace regulations and enforcement, and the state's overall economic and social condition[27].

Company's size has also shown correlation with rate of accidents. According to Eurostat data for 1998 revealed that in the European Union (EU) the majority accidents resulting in more than three days' absence from work or death occurred in companies with between 10 and 49 employees[28].

Other factors can also be connected to safety behaviors and help to evaluate cases of uncertainty or even alert the seriousness of a detected event. For instance, it is more immediately dangerous to life or health not wearing respirators in case of oxygen deficiency environments than when exposed to non-toxic particulate contaminants and

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this knowledge can affect the interpretation of severity when a worker not wearing this equipment in any of those situations is detected. Yet, it is common sense that a worker is exposed to higher risks when the machine which they interact is in operation then when it is switched off; it can modify the state of and event, for instance, from hazard detected to safe if a worker not warning the appropriate PPE is detected interacting with a switched off machine. Fig. 2 shows examples of attributes status, potentially hazardous events being or not detected and the role context may play in each of them.

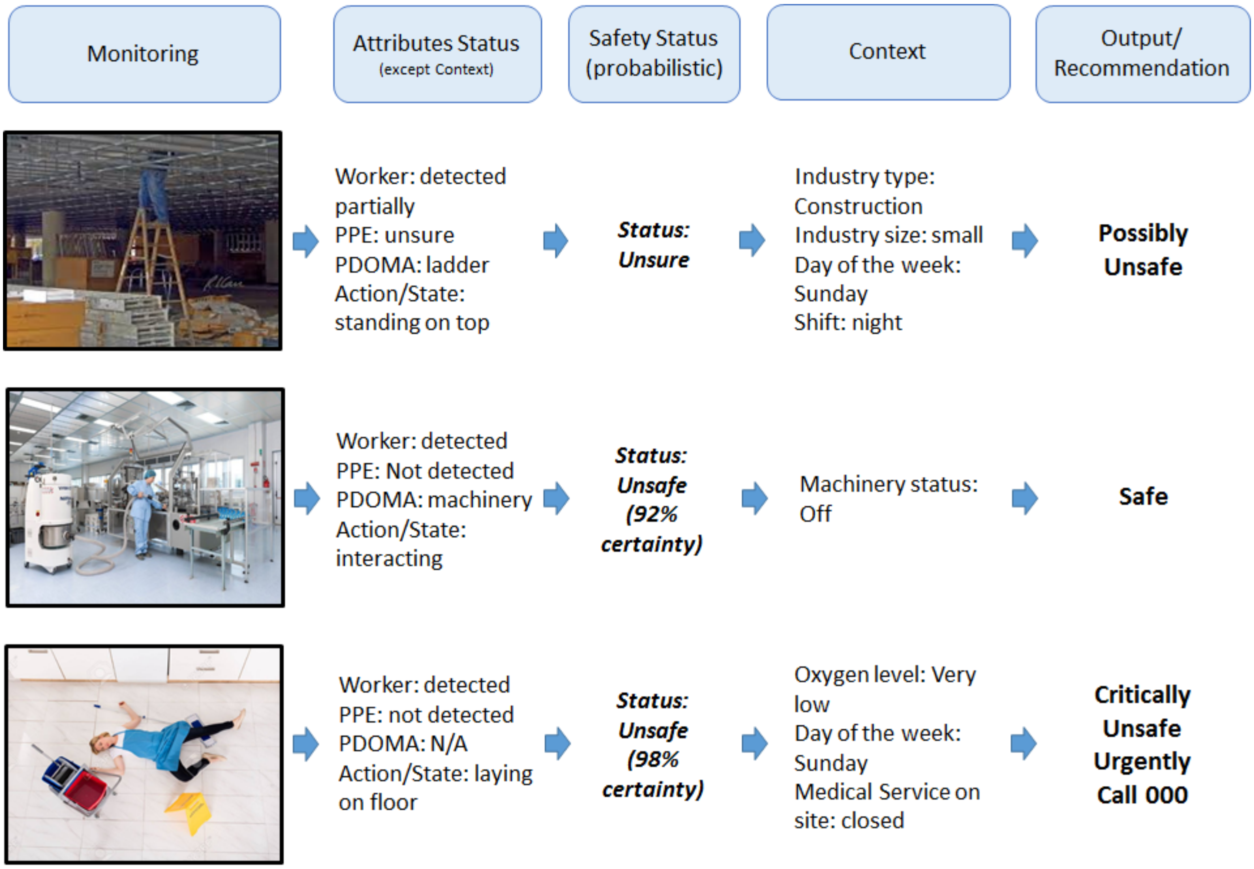

Fig. 2. Examples of potentially hazardous events being or not detected and the role context may play on each of them.

In our platform, workers are continually monitored and, as shown on Fig 2, the status of events being captured (safe or unsafe) can be influenced by the context in which it occurs in real time. For a given set of attributes detected and classified by a Convolutional Neural Network, the safety status will depend on the set of safety rules given during the configuration process, as mentioned previously. When the rules are violated, the captured events are identified as unsafe. Their evaluation will, then, take into consideration the available contextual knowledge, so more accurate and detailed output can be provided to the user.

To create experiences, the contextual knowledge must be represented in an explicit way so it can be readily articulated, codified, accessed and shared. The "explicitness" of a knowledge depends on its nature as well as on the capacity of the system to proceduralize it[22]. Therefore a knowledge representation capable of storing experiences, facilitating sharing at the same time as allows their understanding inside different contexts is essential.

4.2 Modelling and representation of contextual knowledge

Formalizing context has been a central issue of research in artificial intelligence and related areas. Even before acquiring contextual knowledge, the designer faces the representation problem[22]. In our system contextual knowledge is represented explicitly as part of the Set of Experience Knowledge Structure (SOEKS), a knowledge representation structure designed to obtain and store formal decision events in an explicit way. Companies may share certain safety-related experiences, but behavior-based safety situations happening inside of an organization must also be understood in its own context. In addition, organizational safety cultures are usually self-perpetuating, i.e. it is passed along, and new members are coached into the prevailing culture and beliefs which influences their behavior in regards to safety practices. This self-sustaining and perpetuating feature, also means that poor safety cultures can be resistant to change and that modifying the culture can be a very slow process[13]. To create uniqueness contexts, validated SOEKS from each particular organization are grouped and stored as a Decisional DNA (DDNA) a decisional safety fingerprints of a company to support an explicit long term safety culture change process that can be systematically assessed and shared. In addition, when similar events to those stored occurs a quicker and more precise response can be provided.

4.2.1 Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA)

Computers, unfortunately, are still not capable of forming representations of the world as a human being, and even simpler, representations of just formal decision events. Adequately, efficiently, and effectively representing information and knowledge inside a computer is not a trivial process. For this reason, our consideration of using SOEKS as carrier for decisions making is logically founded in the fact that experience has to be taken into account for developing a better cognitive vision system.

The Set of Experience Knowledge Structure SOEKS is a knowledge representation structure designed to obtain and store formal decision events in an explicit way. It is based on four key basic elements of decision-making actions (variables, functions, constraints and rules). Variables are generally used to represent knowledge in an attribute-value form, following the traditional approach for knowledge representation. Given that, the set of Functions, Constraints, and Rules of SOEKS are different ways of relating knowledge variables, it is safe to say that the latter are the central component of the entire knowledge structure. Functions define relations between a dependent variable and a set of input variables; therefore, SOEKS uses functions as a way to create links among variables and to build multi-objective goals. Likewise, constraints are functions that act as a way to limit possibilities, limit the set of possible solutions and control the performance of the system in relation to its goals. Finally, rules are relationships that operate in the universe of variables and express the condition-consequence connection as “if-then-else” and are used to represent inferences and associate actions with the conditions under which they should be implemented[8].

The Decisional DNA consists is a structure capable of capturing decisional fingerprints of an individual or organization and has the Set of Experience Knowledge Structure SOEKS as its foundation. Multiple Sets of Experience, also known as SOE, can be collected, classified, organized and then grouped into decisional chromosomes, which accumulate decisional strategies for a specific area of an organization. The set of chromosomes comprise, finally, what is called the Decisional DNA (DDNA) of the organization[28].

SOEKS and DDNA can be used to solve the scalability issues found in current Computer Vision approaches by introducing an experience based approximation that aims to recognize events defined by the user using the association among variables, production rules, and context, adapting to different conditions, clients and situations. In addition, by creating the safety DDNA of organizations as the system runs, event can be precisely understood inside the companies’ context and information can be safely stored, accessed and shared among computer systems. Fig. 3 illustrates the process of representation of the knowledge as SOEKS and storing as DDNA.

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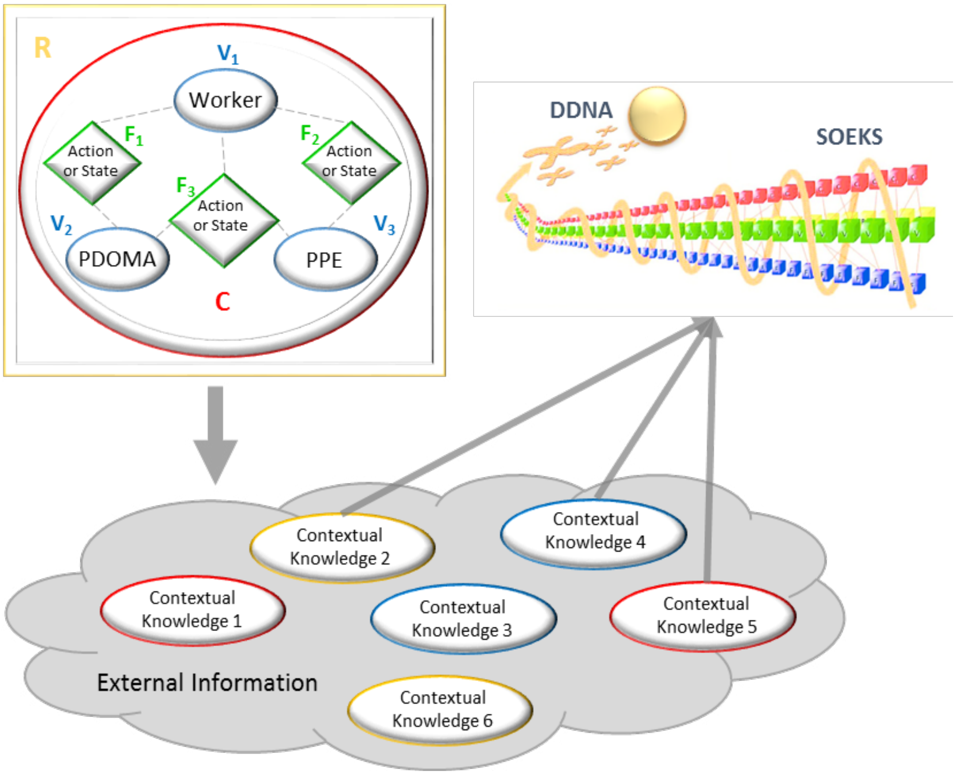

Fig. 3. Representation of the Knowledge as SOEKS and creation of a Decisional DNA (DDNA).

5. Conclusion and Future Work

In this paper we presented a Cognitive Vision Platform for Hazard Control (CVP-HC) with focus in industrial environments. The Cyber Physical System aims to perceives critical safety behaviors in real time giving support for the behavior-based safety strategy whilst stores information in an structured way to support an explicit long term culture change process that can be systematically assessed and shared. The CVP-HC is designed to be a scalable yet adaptable system capable of working in a variety of video analysis scenarios attending specific safety requirements of different industries by modifying its behavior accordingly without the need of recoding the system to better suit every specific application. Additionally, the system attend one of the main characteristics of Cognitive Vision: extendability; which means, it is planned to grown and attend more than what it is initially thought and tested for. The proposed system is based on the Set of Experience Knowledge Structure (SOEKS or SOE in short) and Decisional DNA (DDNA). We highlight in this research the importance of context knowledge to support formal reasoning. Contextual information is sensed or provided to the recognition system through different sources of information and represented explicitly as structured knowledge. These contextual knowledge is then used to characterize and improve the recognition and interpretation of detected events.

At this point the exact influence of contextual knowledge in the decision making was not defined quantitatively. For next steps, tests to measure the gain in accuracy, certainty and interpretation simple events will be evaluated. In addition, the different sources of knowledge proposed in this paper will be thoroughly examined and flow for collection and representation of data designed.

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