CONTEXT IN ROBOTIC VISION: CONTROL FOR REAL-TIME ADAPTATION

Paolo Lombardi
Istituto Trentino di Cultura ITC-irst, via Sommarive 18, Trento, Italy
(*formerly with Dip. Informatica e Sistemistica, Università di Pavia*)

Virginio Cantoni
Dip. Informatica e Sistemistica, Università di Pavia, via Ferrata 1, Pavia, Italy

Bertrand Zavidovique
Institut d'Electronique Fondamentale, Université de Paris Sud-11, bât. 220, Campus d'Orsay, Orsay, France

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Abstract: Nowadays, the computer vision community conducts an effort to produce canny systems able to tackle unconstrained environments. However, the information contained in images is so massive that fast and reliable knowledge extraction is impossible without restricting the range of expected meaningful signals. Inserting a priori knowledge on the operative "context" and adding expectations on object appearances are recognized today as a feasible solution to the problem. This paper attempts to define "context" in robotic vision by introducing a summarizing formalization of previous contributions by multiple authors. Starting from this formalization, we analyze one possible solution to introduce context-dependency in vision: an opportunistic switching strategy that selects the best fitted scenario among a set of pre-compiled configurations. We provide a theoretical framework for "context switching" named *Context Commutation*, grounded on Bayesian theory. Finally, we describe a sample application of the above ideas to improve video surveillance systems based on background subtraction methods.

1 INTRODUCTION

Computer vision was always considered a promising sensor for autonomous robots (e.g. domestic assistant robots, autonomous vehicles, video surveillance robotic systems, and outdoor robotics in general). Such applications require fast and reliable image processing to ensure real-time reaction to other agents around. Meanwhile, robots operating in varying and unpredictable environments need flexible perceptive systems able to cope with sudden context changes. To a certain extent, in robotics flexibility and robustness may be intended as synonyms.

Conciliating real-time operation and flexibility is a major interest for the vision community today. Traditionally, flexibility has been tackled by increasing the complexity and variety of processing stages. Voting schemes and other data fusion methods have been widely experimented. Still, such methods often achieve flexibility at the expense of real time.

Contextual information may open possibilities to improving system adaptability within real-time constraints. A priori information on the current world-state, scene geometry, object appearances, global dynamics, etc may support a concentration of system computational and analytical resources on meaningful components of images and video sequences. The recognition of the current operative "context" may allow a reconfiguration of internal parameters and active processing algorithms so as to maximize the potential of extractable information, meanwhile constraining the total computational load. Hence, "context" recognition and managing has attracted much interest from the robotic vision community in the last two decades.

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A necessary step to implement context-dependency in practical vision system is defining the notion of "context" in robotic vision. Various authors have covered different aspects of this matter. A summarizing operative definition may serve as an interesting contribution and a reference for future work. Furthermore, it helps in identifying possible "context changes" that a system should cope with.

Overall, context managing represents a replacement of parallel image processing with less computationally expensive control. Controlling internal models and observational modalities by swapping among a finite set of pre-compiled configurations is probably the fastest and yet more realistically realizable solution.

In Section 2, we present a wide range of works related to "context" in computer vision. Section 3 details our proposal of formalization of such contributions by describing an operative definition. Then, Section 4 applies these concepts to a realistic implementation of real-time context-dependent adaptation within the scope of Bayesian theory. Finally, Section 5 concludes by suggesting some discussion and presenting future work.

2 CONTEXT IN COMPUTER VISION

In earlier works, contextual information referred to image morphology in pixel neighborhoods, both spatial and temporal. Methods integrating this information include Markov Random Fields (Dubes, 1989), and probabilistic relaxation (Rosenfeld, 1976). More recent works have moved the concept to embrace environmental and modeling aspects rather than raw signal morphology. General typologies of "context" definitions include:

1. *physical world models*: mathematical description of geometry, photometry or radiometry, reflectance, etc – e.g. (Strat, 1993), (Merlo, 1988).
2. *temporal information*: tracking, temporal filtering (e.g. Kalman), previous stable interpretations of images in a sequence, motion behavior of objects, etc – e.g. (Kittler, 1995), (Tissainayagam, 2003).
3. *site knowledge*: specific location knowledge, geography, terrain morphology, topological maps, expectations on occurrence of objects and events, etc – e.g. (Coutelle, 1995), (Torralba, 2003).
4. *scene knowledge*: scene-specific priors, illumination, accidental events (e.g. current weather, wind, shadows), obstacles in the viewfield, etc – e.g. (Strat, 1993).
5. *interpretative models and frames*: object representations (3d-geometry-based, appearance-based), object databases, event databases, color models, etc – e.g. (Kruppa, 2001).
6. *relations among agents and objects*: geometrical relationships, possible actions on objects, relative motion, split-and-merge combinations, intentional vs. random event distinctions, etc – e.g. (Crowley, 2002).
7. *acquisition-device parameters*: photo-grammetric parameters (intrinsic and extrinsic), camera model, resolution, acquisition conditions, daylight/infrared images, date and time of day, etc – e.g. (Strat, 1993), (Shekhar, 1996).
8. *observed variables*: observed cues, local vs. global features, original image vs. transformed image analysis, etc – e.g. (Kittler, 1995).
9. *image understanding algorithms*: observation processes, operator intrinsic characteristics, environmental specialization of individual algorithms, etc – e.g. (Horswill, 1995).
10. *intermediate processing results*: image processing quality, algorithm reliability measures, system self-assessment, etc – e.g. (Draper, 1999), (Rimey, 1993), (Toyama, 2000).
11. *task-related planning and control*: observation tasks, global scene interpretation vs. specialized target or event detection, target tracking, prediction of scene evolution, etc – e.g. (Draper, 1999), (Strat, 1993).
12. *operation-related issues*: computational time, response delay, hardware breakdown probabilities, etc – e.g. (Strat, 1993).
13. *classification and decision techniques*: situation-dependent decision strategies, features and objects classifiers, decision trees, etc – e.g. (Roli, 2001).

Despite definitions of "context" in machine vision have appeared under multiple forms, they all present "context" as an interpretation framework for perceptive inputs, grounding perception with expectation.

Probably a definition of *context* in computer vision, yet rather a non-operative one, could be given by dividing a perceptive system into an *invariant part* and a *variable part*. The *invariant part* includes structure, behaviors and evolutions that are inherent to the system itself, and that are not subject to a possible change, substitution or control. Examples may be the system very hardware, acquisition sensors, and fixed links between them, etc.; basic sub-goals like survival; age, endemic breakdowns, mobility constraints, etc. The *variable* *part* is all parameters, behaviors, and relations between components, which can be controlled. By means of these parts, the system may acquire dependence from the outer world and situation, with the purpose of better interacting with other agents and objects. In this view, *context* is what imposes changes to the *variable part* of a system. When mapped into the system through its variable parts, *context* becomes a particular configuration of internal parameters.

3 AN OPERATIVE DEFINITION OF CONTEXT

Inspired by the partial definitions from the previous references, we propose the following formalization (see (Lombardi, 2003) for details).

Definition D.1: *Context* Q in computer vision is a triplet $Q = (M, Z, D)$, where:

- M is the *model set* of object classes in the environment;
- Z is the *operator set*, i.e. the set of visual modules used in the observation process;
- D is the *decision policy* to distinguish between different classes of objects.

The rationale is that in perceptive systems, elements that can be parameterized and thus controlled are prior models of external objects, models of system components, and the relations among them. In short, D includes all prior assumptions on the strategy for inter-class separation and intra-class characterization. Essentially, it stands for point 13 in the above list. Hereafter, we further specify the definitions of M and Z.

3.1 Model Set M

The *model set* M contains all a priori knowledge of the system regarding the outer scene, object/agent appearances, and relations among objects, agents and events (essentially, points 1-6). We explicitly list three groups of knowledge inside M.

Definition D.2: A *model set* is a triplet $M = (\{m\}, P_{\{m\}}, V_{\{m\}})$, where:

- $\{m\}$ is the *entity knowledge* describing their appearance;
- $P_{\{m\}}$ is the prior expectation of occurrence in the scenario;
- $V_{\{m\}}$ is the *evolution functions* describing the dynamics.

Entity knowledge m indicates the set of features and/or attributes that characterize an object type. Here, we call "entity" (Crowley, 2002) any object, agent, relation, or global scene configuration that is known, and thus recognizable, by the perceptive system. The set of all entity descriptions $\{m\}$ is the total scene-interpretation capability of the system, namely the set of all available a priori models of object classes that the system can give semantics to raw data with. Minsky frames and state vectors containing geometrical information are examples of descriptors. Moreover, the image itself can be thought of as an object, thus $\{m\}$ includes a description of global scene properties.

P_m is the prior expectations on the presence of *entity* m in the scene. We distinguish P_m from m because object descriptions are inherently attached to an *entity*, while its probability of occurrence depends on causes external to objects. *Evolution functions* $V_{\{m\}}$ indicate the set of evolution dynamics of an *entity* state parameters, e.g. object motion models.

3.2 Operator Set Z

The *operator set* Z gathers all prior self-knowledge on the perceptive system, available algorithms and hardware, feature extraction and measurement methods, observation matrixes, etc (points 7-12). We explicitly list three descriptors in Z.

Definition D.3: An *operator set* is a triplet $Z = (\{z\}, H_{\{z\}}, C_{\{z\}})$, where:

- $\{z\}$ is the *operator knowledge* describing their mechanisms;
- $H_{\{z\}}$ are the *operative assumptions* of operators;
- $C_{\{z\}}$ is the *operation cost* paid by system performance to run operators.

Operator knowledge z contains all parameters, extracted features, tractable elaboration noise, and other relevant features of a given visual operator. The set $\{z\}$ spans all visual modules in a system and their relative connections and dependencies. Operators constitute a grammar that allows matching data and semantics (*model set* M). Set $\{z\}$ includes logical operators, relation operators (e.g. detectors of couples), and events detectors.

Operative assumptions H_z is the set of hypotheses for the correct working of a visual module z. Implicit assumptions are present in almost every vision operator (Horswill, 1995). A misuse of z in situations where H_z do not hold true may cause abrupt performance degradation.Parameter C_z is a metrics depending on average performance ratings (e.g. computational time, delay, etc) useful to optimize system resources.

3.3 Contextual Changes

The explicit formulation of D.1 allows for a deeper understanding of *contextual adaptability* problems and of "context changes".

Definition D.4: A *context change* is a change in any component of a *context* Q, and we write it with $\Delta Q = (\Delta\{m\} \| \Delta P_{\{m\}} \| \Delta V_{\{m\}} \| \Delta\{z\} \| \Delta H_{\{z\}} \| \Delta C_{\{z\}} \| \Delta D)$, where || is a logical or.

Each component of ΔQ generates a class of *adaptability problems* analyzed in the literature under an application-specific definition of "context change". Here follow some examples:

a) $\Delta\{m\}$ may occur when i) the camera dramatically changes its point of view, ii) a perceptive system enters a completely different environment of which it lacks some object knowledge, iii) object description criteria become inappropriate.
b) $\Delta P_{\{m\}}$ means that the frequency of an *entity* class occurrence has changed, e.g. i) a camera enters a new geographical environment, ii) stochastic processes of object occurrence are non-stationary in time.
c) $\Delta V_{\{m\}}$ may occur when agents change trajectory so that hybrid tracking is needed – see (Tissainayagam, 2003), (Dessoude, 1993).
d) $\Delta\{z\}$may consist in i) inappropriate modeling of operator mechanisms, ii) inappropriate self-assessment measures, etc.
e) $\Delta H_{\{z\}}$ indicates a failure of assumptions underlying $\{z\}$. For instance, a skin color detector whose color model is inappropriate to lighting conditions – see (Kruppa, 2001).
f) $\Delta C_{\{z\}}$ turns into a resource management problem. Dynamic programming, task planning, parametric control are examples of methods to find the best resource reallocation or sequencing.
g) ΔD may occur when i) assumptions for separation of object classes become inappropriate, ii) critical observed feature become unavailable, iii).

Definition D.5: The problem of insuring reliable system processing in presence of a *context change* is called an *adaptability problem*.

4 BAYESIAN CONTEXT SWITCHING

Two are the solutions to cope with *context changes*: i) a system has available alternative perceptive modalities; ii) a system can develop new perceptive modalities. The latter solution would involve on-line learning and trial-and-error strategies. Although some works have been presented – e.g. genetic programming of visual operators (Ebner, 1999) –, this approach is likely beyond the implementation level at present.

The first solution may be implemented either by using "parallelism" or by "opportunistic switching" to a valid configuration. "Parallelism" consists in introducing redundancy and data fusion by means of alternative algorithms, so that failures of one procedure be balanced by others working correctly. However, parallelism is today often simulated on standard processors, with the inevitable effect of dramatically increasing the computational load at the expense of real time. This feature conflicts with the requirements of machine vision for robotics. "Opportunistic switching" consists in evaluating the applicability of a visual module or in pointing out a change in the environmental context, to commuting the system configuration accordingly. Opposite to parallelism and data fusion, this swapping strategy conciliates robustness and real time. Here we further develop the latter option (4.1), we describe a Bayesian implementation of it (4.2), and finally we exemplify an application to contextual video surveillance (4.3).

4.1 Opportunistic Switching

Opportunistic switching among a set of optimized configurations may ensure acceptable performance over a *finite* range N of pre-identified situations (i.e. "contexts").

Definition D.6: Designing a system for context-dependent *opportunistic switching* consists in building and efficiently controlling a mapping ζ between a set of *contexts* Q and a set of *sub-systems* S, i.e. (1). The switching is triggered by *context changes* D.4.

$$\zeta : Q(t) \rightarrow S(t) \tag{1}$$

Building the map is an application-dependent engineering task: for each typical situation, the perceptive system must be engineered to deliver acceptable results. Control is performed by detecting

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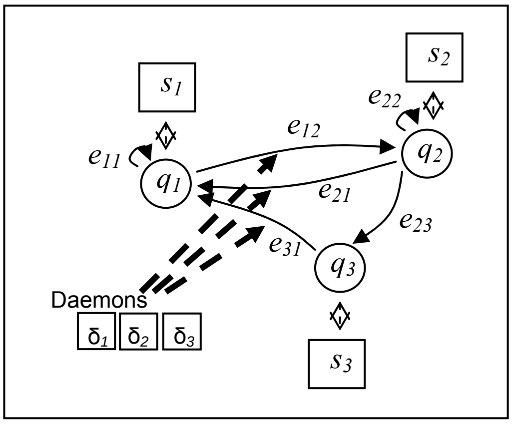


Figure 1: An oriented graph may easily accommodate all the elements of an *opportunistic switching* structure as defined in Section 3: *context*/*sub-system* pairs in nodes, and *events* in arcs. *Daemons* trigger global state change.

the current *context* $Q(t)$, or equivalently by detecting *context changes* ΔQ. A context-adaptable system must be endowed with context-receptive processing, i.e. routines capable of classifying N different *context states* $\{q_1, q_2,... q_N\}$. Essentially, such routines detect "context features", and *context* recognition can be thought of as an object recognition task. The design of such routines appears to be an application-dependent design issue

Definition D.7: Let us name *daemon* an algorithm or sensor δ exclusively dedicated to estimating *context states* q.

Opportunistic switching has two advantageous features: i) *flexibility and real-time*, because multiple configurations run one at a time, and ii) *software reuse*, because an increased flexibility can be achieved by integrating current software with *ad-hoc* configurations for uncovered *contexts*. Assumptions for its use are: i) there exists a rigid (static) mapping from problems to solutions, ii) reliable *context* detection.

4.2 Context Commutation

The mapping ζ and its control may assume the form of parametric control, of knowledge-based algorithm selection, of neural network controlled systems, etc. Hereafter we present a Bayesian implementation of the opportunistic switching strategy, named *Context Commutation* (*CC*) (Lombardi, 2003). It is inspired by hybrid tracking –e.g. (Dessoude, 1993) –, where a swapping among multiple Kalman filters improves tracking of a target moving according to changing regimes.

Context Commutation represents context switching by means of a Hidden Markov Model – e.g. (Rabiner, 1989) –, where the hidden process is *context evolution* in time, and the stochastic observation function is provided by appropriate probabilistic sensor models of *daemons*. Time is ruled by a discrete clock t. Each clock step corresponds to a new processed frame.

Definition D.8: *Context Commutation* represents *context evolution* by means of a discrete, first-order HMM with the following components (Figure 1):

1. A *set of states* $Q = \{q_1, q_2, ...q_N\}$. Each state q_i corresponds to a *context* and gets an associated optimized system configuration s_i. For every i, s_i is such that the perceptive system works satisfactorily in $q_i = \{M_i, Z_i, D_i\}$ i.e. M_i, Z_i, D_i are the appropriate models, operators and decision policies in the i-th situation.
2. An *observation feature space* Φ composed of *daemon* outputs φ. If there are K *daemons*, φ is a K-dimensional vector.
3. A *transition matrix* E, where elements E_{ij} correspond to the a priori probability of transition from q_i to q_j, i.e. (2).

$$E_{ij} = P[e_{ij}] = P[Q(t) = q_j \mid Q(t\text{-}1) = q_i] \qquad (2)$$

4. An *observation probability distribution* $b_i(\varphi)$ for each context q_i, defined in (3). Thus, the N different $b_i(\varphi)$ define the global *daemon* sensor model of Bayesian signal analysis theory.

$$b_i(\varphi) = P(\Phi(t) = \varphi \mid Q(t) = q_i) \qquad (3)$$

5. An *initial state distribution* function $\pi = \{\pi_1, \pi_2, ...\pi_N\}$, where $\pi_i \in [0, 1]$ for $i = 1, 2, ...N$, and (4) holds true.

$$\sum_{i=1}^{N} \pi_i = 1 \qquad (4)$$

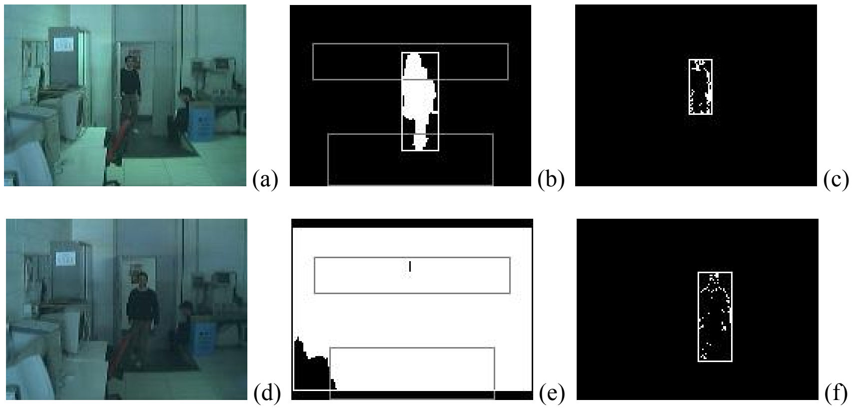


Figure 2: When a reliable background reference model is available (a), background subtraction methods deliver more meaningful motion information (b) than simple frame differencing (c). However, if the lighting conditions suddenly change, e.g. an artificial light is turned off (d), BS fails (e) while FD still works properly.

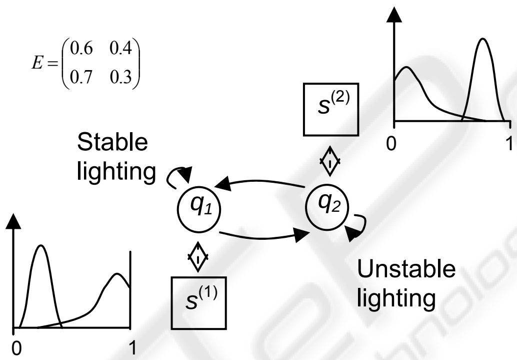


Figure 3: The simple *CC* system for "light switch" problems has two states and one daemon. The picture shows the transition matrix *E* used in the experiments (top left), and a representation of daemon models (next to the s_i boxes).

6. The *current context* q_v is estimated by the Maximum A Posteriori on $\Psi(t)$ (5), (6).

$$\Psi(t) = (P(q_1), P(q_2), \ldots P(q_N)) \tag{5}$$

$$v = \operatorname{argmax}_i [\Psi_i(t)] \tag{6}$$

4.3 A practical implementation

As a final illustration, we demonstrate an application of *Context Commutation* to tackle the "light switch" problem affecting *background subtraction* (BS) for motion detection in automatic video surveillance. In indoor environments, when artificial lights are turned on or off, the reference background model used in BS looses validity in one frame-time. Modern time-adaptive background systems (Stauffer, 1999) usually take around 10÷100 frames to recover. An alternative solution involves the use of a second algorithm that degrades less its performance in case of abruptly changing lighting conditions. For instance, *frame differencing* (FD) algorithms deliver motion information like BS does, and they recover from "light switch" just after 1 frame (Figure 2).

A context-adaptable system based on opportunistic switching would feature two system states: i) using BS when appropriate, ii) using FD otherwise. In the general case, BS delivers a more informing motion map than FD. However, when lighting conditions are unstable, the system swaps to FD – which recovers more quickly.

Here, we design a *CC* system as shown in Table 1 and Figure 3. The two *contexts*, corresponding to "stable" and "unstable" global lighting, cope with a *context change* ΔH_{bs} which corresponds to a failure of a basic *operative assumption* founding BS's correct working – i.e. stable lighting –. The *daemon* δ_1 apt to detecting ΔH_{bs} is modeled with two truncated Gaussians of the kind shown in Figure 3, with parameters tuned by training. *Daemon* δ_1 counts the pixels n_a and n_b showing a luminance change that breaks thresholds $\theta_{\delta 1}$ and $-\theta_{\delta 1}$, respectively: n_a+n_b represents all pixels showing substantial luminance change. The output (7) is then a measure of the luminance unbalance over the last two images. In stable lighting conditions φ_1 would be 0. The closer φ_1 to 1, the more likely switched the light.

$$\varphi_1 = 2\frac{\max(n_a, n_b)}{n_a + n_b} - 1 \qquad (7)$$

Table 1

Q	Situation	S
q_1	stable lighting	BS active if in ready state FD active if BS in recovering state
q_2	unstable lighting	FD active

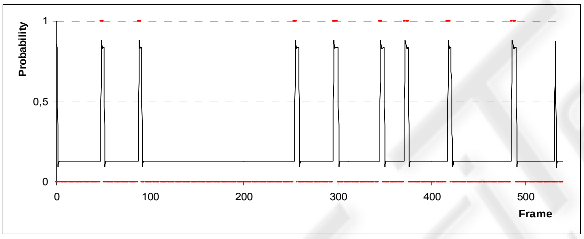
To assess context estimation performance, δ_1 was tested on over 1500 images containing about 50 light switches. The test was done on sequences indexed by a human operator. Figure 4 shows the results on one test sequence: when the confidence rating breaks 0.5, q_2 is estimated. Bold dots on the top line show the ground truth for q_2 occurrence. Model parameters $G_i \sim (\mu_i, \sigma_i)$ in q_i are in Table 2.

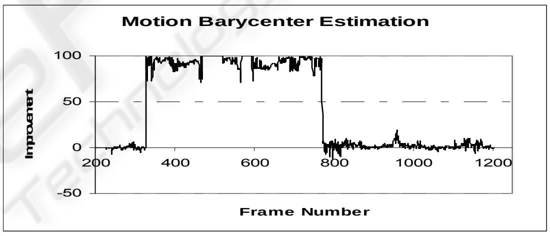
Table 2

	μ_1	μ_2	σ_1	σ_2
δ_1	0.09	0.71	0.17	0.36

We measured an average correct estimation rate of 0.95. The percentage goes up to 0.98 if a 3-frame-range error is allowed in locating the contextual switch. In effect, this error allowance accounts for human mistakes in indexing the test videos.

The motion detection system with and without *CC* was tested on several sequences. No tracking was performed, only motion detection. The graph of Figure 5 shows the improvement provided by *CC* in terms of such distance (when BS failed because of inappropriate background model – e.g. Figure 2 –, the corresponding estimation error was set to 100). Figure 6 shows some results for one sequence where light switches twice: on-off on frame 327, and off-on on frame 713. The distance of the barycentre of motion between automatic detection and human labeling was computed for BS only, and for BS/FD combined by means of *CC*.





Figures 4, 5: Probability that the current *context state* be q2 as estimated by δ_1 in a test sequence (left). Improvement in the estimation error provided by context switching (*CC*) with respect to BS alone (right).

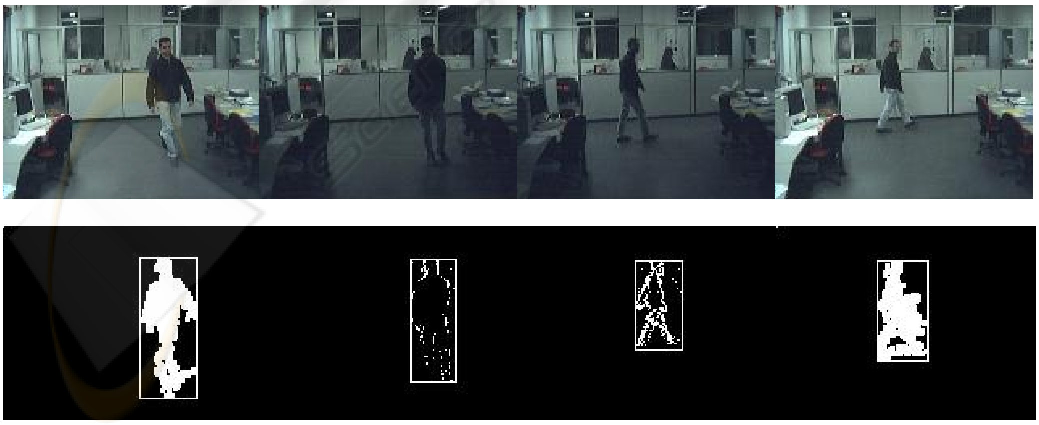


Figure 5: Frames no. 322, 332, 702, and 932 from a test sequence: original images (first row), motion detection by BS and FD managed opportunistically by *CC* (second row).

5 CONCLUSIONS

In this paper we foster deeper studies in the management of contextual information in robotic vision. In the first part, we proposed an operative definition of "context" to identify the variable parts of a perceptive system susceptible of becoming inappropriate in case of contextual changes: models, operators, and decision policies.

In the second part, we described a novel Bayesian framework (i.e. *Context Commutation*) to implement contextual opportunistic switching. Dedicated algorithms, called *daemons*, observe some environmental features showing a correlation with system performance ratings rather than with the target signal (e.g. people tracking). When such features change, the system commutes its state to a more reliable configuration.

Critical points in *Context Commutation* are mainly related to its Bayesian framework. Parameters like sensor models of *daemons* and coefficients of the *transition matrix* need thorough tuning and massive training data. An error in such parameters would corrupt correct contextual switching.

Possible points for future work are: i) exploring switching reliability with incorrect parameters, ii) studying *Context Commutation* with more than eight states, iii) extending the framework to perceptive systems including sensors other than solely vision.

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