ADAPTIVE AGENT BASED SYSTEM FOR STATE ESTIMATION USING DYNAMIC MULTIDIMENSIONAL INFORMATION SOURCES

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Abstract: This paper describes a new approach for the creation of an adaptive system able to selectively combine dynamic multidimensional information sources to perform state estimation. The system proposed is based on an intelligent agent paradigm. Each information source is implemented as an agent that is able to adapt its behavior according to the relevant task and environment constraints. The adaptation is provided by a local self-evaluation function on each agent. Cooperation among the agents is given by a probabilistic scheme that integrates the evidential information provided by them. The proposed system aims to achieve two highly desirable attributes of an engineering system: robustness and efficiency. By combining the outputs of multiple vision modules the assumptions and constrains of each module can be factored out to result in a more robust system overall. Efficiency is still kept through the on-line selection and specialization of the agents. An initial implementation for the case of visual information demonstrates the advantages of the approach for two frequent problems faced by a mobile robot: dynamic target tracking and obstacle detection.

Key Words: intelligent agents, adaptive software, sensor fusion, probabilistic reasoning, particle filter, visual perception.

1. INTRODUCTION

As the state of the art of computing technology is advancing, providing more powerful and affordable machines, computers are becoming widely used in the more diverse aspects of modern society. As computers start to perform new types of tasks in less structured and less predictable environments, there is an increasing need to provide them with a higher degree of awareness about the changing conditions of their virtual or natural surroundings.

From the seemingly endless information paths of Internet to the case of a mobile robot collecting information from its environment, there is an increasing need for the development of automatic tools able to transform sensing information in useful knowledge.

As an example, in the Robotics domain the problem of understanding sensing information from the environment is highly relevant. While today it is possible to equip a robot with many sensors and sophisticated locomotion capabilities, the perception skills of most robots are still rather limited. In order to move robots out of labs to perform useful tasks in natural environments, it is needed to equip them with more powerful perception systems able to acquire useful knowledge from diverse sources of information. Today the main challenge for robots is not the controllability but the observability problem.

Although it is possible to argue in favor of a stateless or pure reactive machine, following the ideas presented in [1], in this paper we claim the need for maintaining an internal representation of the world that summarize the relevant knowledge needed by the agent[1] in order to act with diligence.

The basic scenario is an agent embedded in an unpredictable and dynamic environment. The agent is able to receive different types of information from its environment. As new information arrives the agent goal is to use the more adequate set of information sources in order to update the knowledge about its relevant part of the world.

In this sense our problem can be cast as dynamic state estimation based on multidimensional information sources. The key observation is that as the state of the world evolves the potential knowledge provided by different information sources can change dramatically. As a consequence there is a high variability about the more adequate set of information sources to complete a task. This stressed the need to incorporate suitable

[1] *We refer to these new types of machines as intelligent agents or just agents*

adaptation mechanisms that allow to combine and to select the more appropriate set of information sources in order to perform robust and efficient state estimation.

As an example consider ALVINN [2], a perceptual visual system designed to steer a car in natural environments using a neural net learning algorithm. After training, the main internal features learned by ALVINN were the edges of the road. With this knowledge ALVINN was able to demonstrate a reasonable performance, but it irremediable failed in situations where the edges of the road were obstructed by other passing vehicles, or were missing as on bridges or crossing points.

The main problem with ALVINN was its lack of adaptability to use alternative sources of information such as centerlines, other traffic, roadway signs, and so on. In contrast to ALVINN human drivers are remarkable robust to changes in the driving conditions. This great robustness of the human visual system can be explained by its extreme flexibility to adapt to the changing conditions of the environment by selecting appropriate sources of information.

In this paper we propose a new approach for the creation of an adaptive system able to selectively combine dynamic multidimensional information sources in order to perform state estimation. The system is based on an *intelligent agent*[2] paradigm. Each information source is implemented as an agent that is able to adapt its behavior according to the relevant task and environment constraints. The adaptation is provided by local self-evaluation functions on the agents. These functions are based on considerations about the level of uncertainty present at each time in the state estimation. Cooperation among the agents is given by a probabilistic scheme that integrates the evidential information provided by them.

Using the power of probability theory for representing and reasoning under uncertainty, and elements from information theory to lead the inference engine to prominent hypothesis and information sources, the proposed system aims to achieve two highly desirable attributes of an engineering system: *robustness* and *efficiency.*

[2] *For a definition of an intelligent agent see section 2.1*

By combining the outputs of multiple information sources the assumptions and constrains of each module can be factored out to result in a more robust system overall. Efficiency is still kept through the on-line selection and specialization of the agents according to the quality of the information provided by each of them.

The research proposed in this work is particularly relevant for the case of dynamic visual tasks with a high variability about the subsets of visual attributes that can characterize relevant visual structures. This includes visual tasks such as dynamic target tracking, obstacle detection, and identification of landmarks in natural scenes. In particular, the advantages of the approach proposed here are demonstrated in two frequent problems faced by a mobile robot: dynamic target tracking and obstacle detection.

This paper is organized as follows. Section 2 describes our approach and its main components. Section 3 presents related work. Section 4 describes the implementation of the proposed system for the case of visual information. Section 5 describes the results of our implementation. Finally, section 6 presents conclusions and future lines of research.

2. APPROACH

2.1. Intelligent Agents

Even though there is a diversity of views about the correct definition of an intelligent agent, there is a general agreement that the main features that distinguish an intelligent agent are *autonomy, sociability, and adaptation* [3]. Autonomy provides the independency that allows the agent to exhibit an opportunistic behavior in agreement with its goals. Sociability provides the communication skills that allow the agent to interact with other artificial agents and humans. Adaptation provides the flexibility that allows the agent to change its behavior according to the conditions of the environment.

This work makes use of multiple agents that can simultaneously analyze different dimensions of the incoming information. These agents act as a group of experts where each agent have a specific knowledge area. This scheme provides a high degree of abstraction and modularity, which facilitate the design and scalability of the system.

2.2. Representation

Bayesian theory provides a solid mathematical framework for reasoning under uncertainty. Using the language of probability theory, a Bayesian approach provides mechanisms to combine information in order to reason about different hypothetical solutions to a problem.

In a Bayesian framework to dynamic state estimation the goal is to use the information available or evidence (e) to keep track of a probability density function (pdf) over a set of possible hypothesis (*h*) of the state of the world.

The core of the Bayesian technique is the so-called Bayes' Rule :

$$P(h/e) = \frac{P(e/h) * P(h)}{P(e)} = \alpha * P(e/h) * P(h) \qquad (1)$$

Bayes rules allows a convenient way to perform state estimation in terms of a likelihood function *P(e/h),* and an a priori term *P(h).* Equation (1) can be easily extended to the dynamic case:

$$P(h_t/\vec{e}_t) = \beta * P(e_t/h_t, \vec{e}_{t-1}) * P(h_t/\vec{e}_{t-1}) \qquad (2)$$

Assuming that the current evidence e_t can be totally explained by the current hypothesis h_t, and that the dynamic of the system follows a first order Markov process, it is possible to obtain (5) which is the standard way to perform Bayesian inference for the dynamic case.

$$P(h_t/\vec{e}_t) = \beta * P(e_t/h_t) * P(h_t/\vec{e}_{t-1}) \qquad (3)$$

$$P(h_t/\vec{e}_t) = \beta * P(e_t/h_t) * \sum_{h_{t-1}} P(h_t/h_{t-1}, \vec{e}_{t-1}) * P(h_{t-1}/\vec{e}_{t-1}) \qquad (4)$$

$$P(h_t/\vec{e}_t) = \beta * P(e_t/h_t) * \sum_{h_{t-1}} P(h_t/h_{t-1}) * P(h_{t-1}/\vec{e}_{t-1}) \qquad (5)$$

The recursive formulation of equation (5) requires knowledge about the observation model $P(e_t / h_t)$ and the system dynamics $P(h_t / h_{t-1})$. In practice, excepting the case of some finite state-space Hidden Markov models, the full Bayesian inference is only possible when the models have suitable analytical expressions. The more typical case is linear-gaussian models. For this case the state pdf remains Gaussian at all times, and the well-known Kalman Filter gives the optimal solution. For the case of nonlinear models it is possible to use the Extended Kalman Filter but still under a Gaussian assumption.

The Gaussian assumption severely limits the use of Bayesian inference for state estimation. High ambiguity is one of the inherent features that emerges in most unstructured environments. In this case the state pdf can have a complex multi-modal shape that cannot be accurately modeled by a Gaussian density. Fortunally stochastic sampling provides an alternative and efficient estimation approach for these cases.

In stochastic sampling a pdf is represented through a set of samples, each with an associated weight representing its probability. The great advantage is that it is possible to approximate any functional non-linearity and system or measurement noise. In this paper we approximate equation (5) using a particle filter approach, also known in the literature as bootstrap filter [4], condensation algorithm [5], or sequential Monte Carlo [6].

Figure 1 shows pseudo code for the operation of the algorithm. Starting from an initial set of samples that approximate the state pdf, the algorithm uses the system dynamic and its current belief to propagate the more prominent hypothesis. Then these candidate hypotheses are weighted according to the support received by the new incoming evidence represented as a likelihood function. The nice feature about the particle filter is the dynamic allocation of the sample hypothesis according to the current belief. This helps to avoid the problem of sample depletion, and allows a great efficiency in the representation in contrast to other stochastic sampling algorithms such as likelihood weighting.

Gordon et al. [4] originally presented this algorithm using some results by Smith and Gelfand. Isard and Blake [5] validated the filter using the factored sampling algorithm. Soto [7] presented a justification based on the composition algorithm. Recently independent results by Doucet [8] and Liu et al. [9] presented an interesting alternative view of the algorithm in terms of sequential importance sampling with resampling.

In summary, to be able to keep a sample version of the posterior density using a particle filter, one needs an initial approximation of the posterior density, and knowledge about how to evaluate the likelihood and propagation densities $P(e_t / h_t)$ and $P(h_t / h_{t-1})$. In general the dynamic of the process determine the level of exploration for new hypothesis, while the likelihood function can be obtained through an adequate metric that evaluates the fitness between each sample hypotheses and the observations. Section 4 describes an implementation of the algorithm and these functions for the case of multidimensional visual information.

At $t = 0$

Sample $h_i\big|_{i=1}^{n}$ *from initial prior* $p(h)$

set $L_t = \{\pi_i, h_i\}\big|_{i=1}^{n}$ *with* $\pi_i = p(h_i)$

For $t = 1,2,...$

  For $i = 1$ *to* n

    Sample $h_{i-} \sim L_t$

    Sample $h_i \sim P(h_i / h_{i-})$

    Evaluate $\pi_i = P(e_t / h_i)$

  end

  Normalize weights $\pi_i = \dfrac{\pi_i}{\sum_i \pi_i}$

  Set new $L_t = \{\pi_i, h_i\}\big|_{i=1}^{n}$

end

Figure1. Pseudo code for Particle Filter algorithm.

2.3. Integration

The integration of information is performed using Bayes nets. Bayes nets take advantage of causal relations among random variables to allow an efficient graphical representation of joint probability distributions (jpds). The efficiency is gained by use of causal knowledge that provides conditional independence relations between the random variables. These independence relations allow partitioning the jpds in simpler local probabilistic models.

Figure 2 shows the typical tree structure of the Bayes nets relevant to this work. Agent nodes directly measure different dimensions of the incoming information. Abstraction nodes allow the integration of information and the updating of the state representation. Also, abstraction nodes allow introducing conditional independence relations among the agents. This decoupling of the information provided by the agents facilitates the construction of probabilistic models for applying Bayesian inference using equation (5).

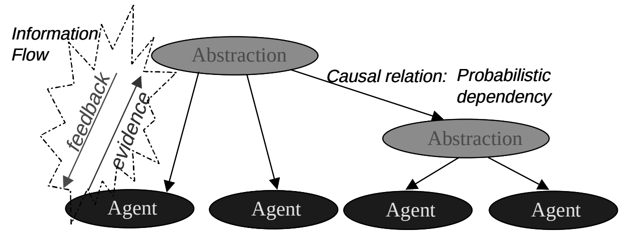

Figure2. Bayes Net

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Figure 2 can be considered as a hierarchical representation of the simpler case of just one abstraction node. In this case equation (5) can be expressed as:

$$P(h_t / \vec{e}_{1,t}, \vec{e}_{2,t}, ...) = \beta * \overbrace{P(e_{1,t} / h_t) * P(e_{2,t} / h_t)}^{Agents} * ...$$

$$... * \underbrace{\sum_{h_{t-1}} P(h_t / h_{t-1}) * P(h_{t-1} / \vec{e}_{1,t-1}, \vec{e}_{2,t-1}, ...)}_{Abstraction\ node} \quad (6)$$

Equation (6) shows the nice decoupling between the evidence provided by each agent through a likelihood function, and the state updating performed by the abstraction node. The abstraction node acts as a central inference that keeps track of the state estimation represented by a set of sample hypothesis and their probabilities. Using the current estimations and the system dynamics, the abstraction node decides which hypothesis need further considerations and it sends this new set of hypothesis to each of the agents. According to its own local information sources, each agent evaluates the supporting evidence for each hypothesis, and it sends this evidence back to the abstraction node as a likelihood function. Finally the abstraction node uses this information to update its beliefs about the state of the world, and it starts a new iteration of the state estimation.

2.4. Adaptation

In contrast to most traditional applications of Bayes nets, where the structures of the nets are fix, the system intended in this research includes adaptation mechanisms that allows dynamic reconfiguration of the nets according to the characteristics of the incoming information.

The adaptation mechanisms are based on the evaluation of the level of uncertainty present in the state estimation and the evaluation of the quality of the information provided by each agent in terms of uncertainty reduction. The design goals are to perform a robust estimation keeping uncertainty low, and also to perform an efficient estimation avoiding the processing of irrelevant, misleading, or redundant information. In order to achieve these goals it is needed to introduce two performance metrics.

The first metric called uncertainty deviation (UD) is intended to evaluate the level of uncertainty in the state representation. The intuition behind this metric is to quantify the dispersion of the state representation with respect to the most probable hypothesis known as maximum a posteriori hypothesis (MAP). Equation (7) shows this metric; here *d* corresponds to a distance metric between hypotheses. In the implementation presented in this work for the case of visual information, *d* corresponds to the Mahalanobis distance[10].

$$UD = \sqrt{\sum_{h_i}^{|h|} d(h_i, MAP) * Pr(h_i)} \qquad (7)$$

The second metric is intended to evaluate the quality of the information provided by each agent in terms of uncertainty reduction. The intuition is that if an agent is providing good information its local likelihood should be close to the state pdf maintained by the abstraction node. So the problem reduces to quantify similarity between distributions. In this work we compare distributions using the Kullback-Leibler divergence [11], which is given by equation (8).

$$D(f, g) = \sum_i f(i) * \log \frac{f(i)}{g(i)} \qquad (8)$$

f(i)= pdf for the state estimation
g(i)= local normalized agent likelihood

Using the previous performance metrics we introduce two adaptation schemes to the state estimation. The first scheme is performed by the abstraction node. Using the UD metric the abstraction node measures the level of ambiguity in its state representation. If this level exceeds a predefined threshold the central inference sends an activation signal to any inactive agent to start sending supporting evidence that can eventually reduce the current ambiguities. Also, in case that this level is lower than a predefined threshold, meaning that the uncertainty is low, the abstraction node stops the less informative agent in order to increase the efficiency of the state estimation. The selection of the less informative agent is performed in base to the relative values of the Kullback-Leibler divergence among the active agents.

The second adaptation scheme is carry out locally by each agent using the UD metric. In this case, given that each agent calculates a likelihood function, the MAP is replaced in equation (7) by the maximum likelihood hypothesis (ML). Using this metric each agent evaluates the local level of uncertainty in its information sources. If this level exceeds a predefined threshold the agent modify its own local actions in order to improve its performance. In case that after a number of cycles the agent still cannot improve its performance, it stops processing information becoming an inactive agent.

Section 4 describes an implementation of these adaptation mechanisms for the case of visual information.

3. Related Work

The idea of reducing uncertainty by combining knowledge from difference sources is by not account new. In several fields it is possible to find studies that recognize the relevance of integrating information in order to create more robust and flexible systems. Although all the abundant literature, there have been a gap between the conceptual idea and the production of working systems for real problems. Important issues such as the organization and control of the pieces of knowledge, and in special the development of mechanisms that allow the adaptation and feedback among the knowledge sources have not been tackled in depth, and they are still open questions. This section reviews some of the efforts that have been appeared in the scientific literature of related fields.

3.1. Artificial Intelligence (AI)

In the AI domain the blackboard model for problem solving is one of the first attempts to adaptively integrate different types of knowledge sources. Using ideas independently proposed by Newell [12] and Simmon [13], Reddy and Erman implemented the first blackboard system as part of the HEARSAY and HEARSAY II speech understanding programs [14][15].

A blackboard model consists of 3 major components: the knowledge sources, the blackboard, and the control unit. A blackboard model divides a problem in *knowledge sources*, which are kept separate and independent. These knowledge sources interact through a *blackboard*, which is the global database that integrates the information. Finally, a *control unit* manages the opportunistic activation of the knowledge sources according to changes in the blackboard.

The blackboard conceptualization is closely related to the ideas presented in this work, but as a problem-solving scheme the blackboard model offers just a conceptual framework for formulating solutions to problems. In this sense, the work proposed in this research aims to extent the blackboard conceptualization to a computational specification or working system, providing specific mechanisms to perform probabilistic inference and adaptive integration for the case of dynamic multidimensional information sources.

3.2. Machine Learning

In the machine learning literature there are been related work in the context of ensembles of classifiers. An ensemble of classifiers is a set of classifiers whose individual decisions are combined to classify new examples [16]. Each classifier can be considered as a different source of knowledge. Adaptation mechanisms are usually included in the policy used to combine the outputs of the individual classifiers. These kinds of techniques are currently receiving broad attention in the machine learning literature due to the capacity of the ensemble to improve performance over the individual classifiers that make them up. There have been several algorithms proposed to implement the ensemble of classifiers; among the more relevant are *Mixture of Experts* [17] and *AdaBoost* [18].

The work presented in this proposal differs in many ways with respect to the current algorithms used to build ensemble of classifiers. One of the main differences resides in the adaptation mechanisms. An ensemble of classifiers is an eager learner in the sense that the training is performed off-line and during operation each classifier acts as a blind data driven box. In contrast, one of the main features of the work proposed here is the on-line interaction or feedback between the knowledge sources.

3.3. Computer Vision

In the computer vision literature there have been a constant acknowledge about the importance of integrating information from different visual dimensions such as depth, color, shape, and so on. Several researchers have proposed a model of visual perception as a distributed collection of task-specific, task-driven visual routines with strong feedback among the visual modules [19][20]. However, all this constant acknowledge, there have been not many working systems that exploit these ideas and most of the work has been concentrated in the development of algorithms to extract knowledge from single visual cues.

Among the relevant works that have shown the gain in robustness of combining several visual modules, it is possible to mention [21][22][23][24]. Unfortunally, most of these works have not considered in their systems topics such as adaptation and uncertainty, being the works by Isard and Blake [5], and Rasmussen and Hager [23] some of the notable exceptions.

4. IMPLEMENTATION

An initial implementation of the ideas presented in this work has been developed for the case of visual information.

In contrast to other sensor modalities, vision can allow the perception of a large number of different features of the environment such as color, shape, depth, motion, and so on. Depending on the task and the environment, the quantity of information or entropy in each visual cue can fluctuate. For instance, while stereovision is usually a strong depth cue, in the case of images from a homogeneous grass field, the stereo decoding of depth is highly noisy. Even worse, it usually gives wrong information due to bad matches. Instead, in this case a visual cue such as texture or color conveys higher entropy.

An efficient integration of visual cues able to adapt to the changing conditions of the environment should increase the robustness of current visual system to successfully operate in natural environments. Following these ideas and using the state estimation presented in this work, we have developed an initial implementation of a visual system for online tracking of dynamic targets and obstacle avoidance.

4.1. State Representation

Bounding boxes were used to describe the state of a tracked target or a detected obstacle. These bounding boxes were modeled by their center position (x,y), width, and height. The rectangular box in figure 3 shows an example of a hypothesis used to perform state estimation. In all the examples shown in this work the state pdf was approximated using 1000 samples. Also for the dynamic of the system we use a stationary Gaussian model with sigma equal to 20 pixels.

4.2. Visual Agents

At this moment the implementation is based on two visual agents: Color Agent and Stereovision Agent.

4.2.1 Color Agent

The color agent uses as observation the hue histogram of the pixels inside each hypothesis in the sample set. A detailed description of the way in which we construct these histograms can be found in [25].

In order to express its observations in terms of a likelihood function, the color agent calculates the similarity between each hypothesis and a reference histogram. The metric used to evaluate similarity is a modified version of the cross similarity distance (csd) using a sigmoid type of function. The introduction of a sigmoid function allows accounting for slight variations in the image conditions and target appearance providing a more accurate probabilistic model. Equations (9) and (10) shows the likelihood function for the case of the color agent. Here all the histograms are previously normalized to the size of the reference histogram.

$$csd = (f_{cum}, g_{cum}) = \sum_{i=1}^{256} |f_{cum}(i) - g_{cum}(i)| \quad (9)$$

$$f_{cum}, g_{cum} := cummulative\ histograms$$

$$Likelihood = 1.0 - tanh(\ 2.0 * \frac{(csd - cte)}{cte}) \quad (10)$$

A special agent called a detector selects the reference histogram automatically. The idea here is to divide the agents in two types: detectors and specialists. Detector agents are general tools able to explore the incoming information looking for possible structures without relying in specific illumination, views, posture, etc. Once possible candidate structures have been identified, it is possible to use specialist agents. These agents are more specific tools able to look for specific supporting evidence in order to provide more efficient and robust appearance models. In the case of color information the detector agent is based on a color segmentation algorithm based on the hue color component [25], while the color specialist agent is the one that estimates the likelihood function described above.

Figure 3 shows the reference and a hypothesis for the case of target tracking. The upper figure corresponds to the initial detection of a detector agent, while the lower one shows the csd and likelihood estimated by the specialist agent.

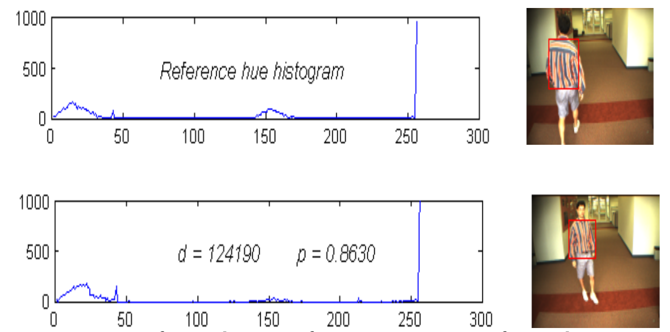

Figure 3. Upper figure shows a reference target. Lower figure shows a state hypothesis.

4.2.2. Stereovision Agent

The stereovision agent uses as observation the depth values of the pixels inside each hypothesis in the sample set. The algorithm is based on depth segmentation and blob analysis, a detailed description of the algorithm can be found in [25].

In order to express its observations in terms of a likelihood function, the stereovision agent estimates four properties of the depth values: depth variance, heights of the depth blobs, blob shape, and number of points with valid depth values. Using these depth features the stereovision agent estimate a likelihood function using a multivariate Gaussian pdf given by equation (11):

$$Likelihood(\vartheta) = \frac{exp\{-0.5*(\vartheta - \mu)^T * B^{-1} * (\vartheta - \mu)\}}{(2\pi)^{1/2}\,|B|^{1/2}} \quad (11)$$

$$\vartheta = feature\ vector\ (depth, height, blob\ shape, valid\ points)$$

$$\mu = mean\ of\ \ feature\ vectors$$

$$B = diagonal\ covariance\ matrix$$

In the case of depth information there is also a detector agent. This agent initializes candidate targets or obstacles using the results of the depth based segmentation algorithm.

4.3. Software Architecture

The core of the software architecture is called CyberAries (Autonomous Reconnaissance and Intelligent Exploration System) which is a distributed multi-agent architecture develop by our research group [26][27]. CyberAries provides powerful inter-agent communication capabilities that greatly simplify the job of developing ensembles of cooperating agents.

On Cyberaries agents are independent processes that run concurrently and can be started on as-needed basis. The software mainly consists of an agent-framework environment and a distribution layer. The agent-framework provides all the operating system provisions such as concurrent processing or automatic scheduling, and also the application abstraction provisions such as memory management and resource categorization. The distribution layer is responsible for providing and balancing the communications, processing, and sensing resources among the active agents. If an agent needs to send a message or to access any resource, the distribution layer handles all the details of the connection, checking for availability and resource allocation.

5. RESULTS

A preliminary version of the system proposed in this work has been developed for the case of single person tracking and obstacle detection.

Figure 4 shows four frames of the video sequence used for the case of single person tacking. The image at the upper left shows the intended target. After an initial detection given by the stereovision agent detector the system starts the tracking using the color and the stereovision specialist agents. The left image in figure 5 shows the set of sample used for the state estimation at frame 4, while the right image shows the MAP estimator for this case.

Figure 4. Four frames of the video sequence used for target tracking

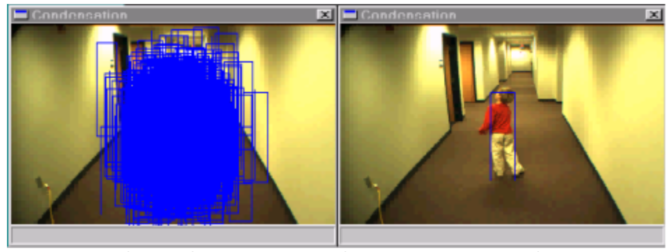

Figure 5. (Left) set of hypothesis used for state estimation at frame 4. (Right) MAP hypothesis at frame 4.

Due to the low ambiguity in the state representation, after five frames the system decided to operate just with the stereovision agent. In this case the system decided to discard the color agent due to the similarities between the color of the target and the rest of the scene. Figure 6 shows the normalized likelihood function provided by the stereovision and the color agents at frame 5. The clear unimodal shape of the likelihood function provided by the stereovision agent shows the low uncertainty present in the depth information. In the same way the highly spread shape of the color likelihood shows the high ambiguity present in the color information. In this case the difference in the level of ambiguity is properly captured by the UD index that it is used to stop the color agent.

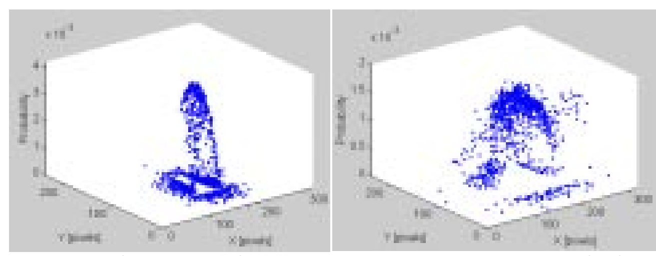

Figure 6. (Left) likelihood function provided by stereovision agent for frame 5. (Right) likelihood function provided by color agent for frame 5. (for clarity only x and y are presented)

On frame 60 a second target enters the scene increasing the uncertainty in the state estimation based only on depth information. This is clearly shown in figure 7 by the bimodal shape of the state estimation. At this point the system automatically starts the color agent at frame 65. The 5-frame delay is set just to avoid unnecessary activations due to noise. Given that the color information of the distracting target differs from the intended target, the additional information provided by the color agent allows a drastic reduction in the uncertainty present in the state estimation (see figure 9).

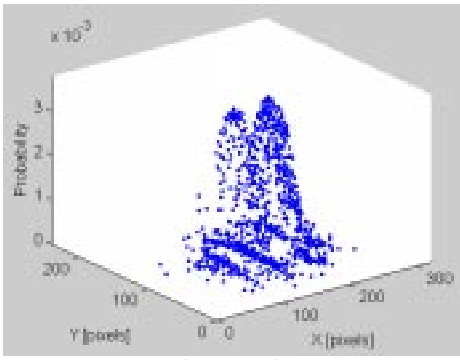

Figure 7. State estimation at frame 60 (for clarity only x and y are presented)

As the second target moves away, the level of uncertainty decreases and the system again decided to operate just with the stereovision agent. Figure 8 shows the activation condition of the color agents for the whole sequence. Figure 9 shows the history of the UD index calculated at the abstraction node.

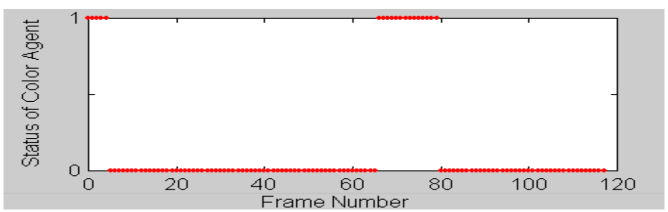

Figure 8. Status of Color Agent (Active=1).

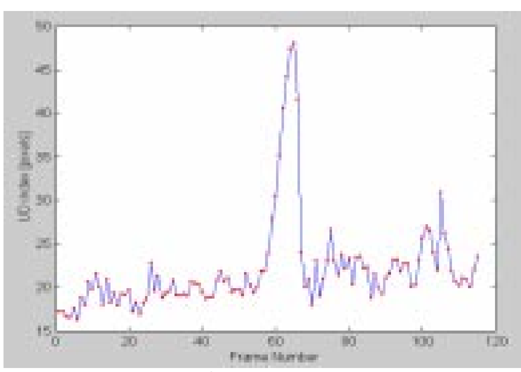

Figure 9. Evolution of the UD index at the abstraction node.

Table 1 shows the different performance in terms of average uncertainty and processing time for four tracking schemes: using just the color agent, using just the stereovision agent, combining the color and stereovision agents without adaptation, and using an adaptive integration of the color and stereovision agent. The important observation is that the adaptive integration of the information provided by the agents not only increases the performance of the system in terms of processing time, but also increase the robustness in terms of average uncertainty by considering the less reliable information provided by the color agent just when it was need it.

Modality	Average Uncertainty	Proceesing Time [hz] *
Color	67.4589 pix	5.23
Stereo	30.7798 pix	2.17
Color + Stereo	29.1677 pix	0.54
Color + Stereo (Ad)	24.7260 pix	2.11

*Pentium 600

Table 1. Comparative results for different operation cases.

Figure 10 shows an example of the performance of the system for the detection of obstacles using stereo and color information. The upper images show the detection based only on stereo for different time instants in the video sequence. From this figure it is clear that the effect of noise makes not possible a robust tracking of the features using just the stereo agent. The lower images show the combined tracking based on the color and the stereo agents. Combining both cues the system was able to keep track of all the structures during the complete video sequence consisting of 40 video frames.

Figure 10. Upper images show the structures detected by the stereo agent at some points during the robot motion. Lower images show the detection of the obstacles for the initial and final frame in the video sequence using information from the color and the stereo agents.

6. Conclusions and Future Work

This paper presented a new approach for state estimation based on the adaptive integration of dynamic multidimensional information sources. Using a synergistic combination of elements from probabilistic Bayesian reasoning and information theory the system allows the creation of a *robust* and *efficient* state estimation system.

The use of a probabilistic representation allows the introduction of uncertainty metrics able to quantify the quality of the information used in the state estimation. Furthermore the use of Bayesian reasoning in combination with an intelligent agent paradigm facilitates the design and scalability of the system. We believe that this is a natural and sound methodology to adaptively combine multidimensional information sources.

An initial implementation of the system for the case of visual information showed encouraging results. The comparative analysis with respect to the case of operation without adaptation and/or integration shows that the adaptive integration of information increases the robustness and efficiency of the system in terms of accuracy and output rate.

There are still further research avenues to improve the system. At this moment the determination of the adaptation thresholds is learned by examples. We are currently working in an automatic determination of these thresholds in based to an optimization function that considers performance requirements in terms of accuracy and output rate. Also at this moment the policy to active agent is fix. We are currently working in the implementation of learning algorithms to optimize the agent switching. The adaptive selection of the optimal number of samples used for the state representation is another important issue to consider because this variable plays an important role in the computational complexity of the system.

For the particular case of visual information, we are currently adding more information sources to the system. In particular we are adding agent based on motion, shape, and texture. Also for the case of multiple targets tracking it is important to add reasoning schemes for the case of target occlusion.

We strongly believe that a synergistic combination of elements from computer vision, intelligent agents technology, probabilistic reasoning, and information theory is a viable way for the creation of a *flexible*, *robust* and *efficient* vision system.

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