© Strojniški vestnik 49(2003)1,52-62
ISSN 0039-2480
UDK 658.515:007.52:519.65
Pregledni znanstveni članek (1.02)

© Journal of Mechanical Engineering 49(2003)1,52-62
ISSN 0039-2480
UDC 658.515:007.52:519.65
Review scientific paper (1.02)

Robotiziran montažni sistem kot sodelujoča večdelna organizacija

A Study of a Robotic Assembly System as a Collaborative Multi-Agent Organization

Jerbić Bojan - Vranješ Božo

Prispevek obravnava načrtovanje večglavega robotiziranega montažnega sistema. Vsak sistem, ki ga je mogoče razstaviti na komponente, lahko obravnavamo kot družbo članov. Takšna zgradba omogoča oblikovanje sodelujočega sistema, ki omogoča nastanek socialne inteligence. Socialno obnašanje je najvišja oblika inteligence, ki omogoča reševanje zelo zapletenih problemov, avtonomno ustvarjanje novih postopkov in učinkovito prilagajanje novim zahtevam. Obravnavani večdelni model temelji na procesnih enotah, ki vsebujejo opremo za prepoznavanje, strategije za reševanje problemov in zmožnost učenja. Sistem ima tako zmožnosti: zaznavanja, prepoznavanja, reševanja problemov, učenja in komunikacije. Uporabljena je okrepljena metoda učenja za vrednotenje delovanja robota in za ustvarjanje novega ali izboljšanje sedanjega znanja. Tako pridobljen vzorec delovanja je spravljen kot izkušnja, ki jo je mogoče uporabiti za reševanje podobnih prihodnjih problemov. Za prepoznavanje podobnosti problemov je uporabljena prilagodljiva mehka senčena (PSMM) nevronska mreža.

(Ključne besede: montaža robotizirana, sistemi večdeln, član neodvisni, metode učenja, mreže nevronalne)

This paper looks at designing a robotic assembly system as a multi-agent system. Any multi-device system, or any system whose performance is naturally decomposable, can be interpreted as a corporation of agents. Such a scheme comprises the ability to create a collaborative system that can provide the achieving of the social intelligence. Social behavior is the highest form of intelligence, which is able to solve very complex problems, autonomously create new procedures and efficiently adapt to new tasks. The presented multi-agent model is based on processing units that include recognition networks, problem-solving strategies and learning engines. It integrates perception, recognition, problem-solving, learning and communication capabilities. The reinforcement learning method is used here to evaluate the robot is behavior and to induce new, or improve the existing, knowledge. The acquired action (task) plan is stored as experience, which can be used in solving similar problems in the future. To recognize problem similarities we applied the Adaptive Fuzzy Shadowed (AFS) neural network.

(Keywords: robotic assembly, multiagent systems, autonomous agent, learning methods, neural networks)

0 UVOD

Sedanji robotizirani montažni sistemi, tudi če so opremljeni z umetnim vidom in drugimi sistemi zaznavanja, so zelo občutljivi za spremembe izdelka ali postopka. Tudi majhne spremembe v geometrijski obliki izdelka povzročijo občutne spremembe montažnega postopka, zamenjavo geometrijske oblike orodij ali strukture delovnega okolja. Kljub digitalni določenosti avtomatskih sistemov povzroči deterministični kaos nepredvidljiva stanja. Običajno se postopek ustavi, ali pa pride do napačne montaže. Zato je razvoj avtonomnega delovanja robotov ključen za avtomatizacijo montažnega postopka. Od

0 INTRODUCTION

Real robotic assembly systems, even those equipped with vision and other perception systems, are still very sensitive to product or process changes. Even small changes in product geometry can imply considerable modifications to the assembly process, an alteration to the tool's geometry or the structure of the working environment. At the same time, in spite of the digital determinism of automatic systems, deterministic chaos produces unpredictable conditions. It usually stops the process or results in defect assemblies. As a result, the development of autonomous robot behavior is a key approach in assembly-system automation. The planning of intelligent robot behavior can be seen as a kind of inteligentnega robota pričakujemo, da se bo obnašal podobno kakor človek, če bo soočen z nepoznanim problemom. Kot prvo se pojavi vprašanje, kako je mogoče zgraditi bazo znanja o nečem, kar je nepoznano, in kako naučiti robota, da bo reševal nepoznane probleme? Edini logični odgovor je: *Robota je treba naučiti, da se bo sam učil.*

1 ROBOTI Z NEODVISNIM OBNAŠANJEM

Neodvisni robot pomeni delovno napravo z določenimi gibalnimi zmožnostmi (premikanje in/ali gibanje), z uporabo ustvarjalnega sistema načrtovanja, ki se odziva na spremenljivo okolje v dejanskem času. Podana definicija opisuje inteligentnega dejavnika z modelom reagiranja, ki temelji na sklopu verjeti - hoteti - nameravati. Običajno ga imenujemo "softbot", robot, temelječ na obnašanju ali bitje z zmožnostjo odločanja, "razumno" bitje. V smislu avtomatske montaže, mora neodvisni dejavnik izkazovati metode prilagajanja in načrtovanja kot odgovor na nedoločeno dinamiko delovnega okolja.

Zapletenost intelektualnih mehanizmov kaže, da je želja razviti model umetne inteligence obsojena na neuspeh in razočaranje. Čar inteligence temelji na dolgotrajnem učnem postopku. Naše ustvarjalno vodilo je prevladujoče predvsem v domeni učenja [3]. Kaže, da so modeli učenja bolj pregledni in laže razumljivi, ker jih je mogoče opazovati, v nasprotju s skritimi možganskimi aktivnostmi [2]. Zato je dosti bolj uspešno ustvariti učeči se sistem, ki je sam zmožen razviti pripadajoče intelektualne mehanizme. Sistem te vrste je mogoče učiti ali izuriti, namesto da bi ga programirali. Učenje za izboljšanje zmožnosti in mehka logika so preverjene metode v inteligentni robotiki [7]. Najboljši rezultati so doseženi na področju mobilnih robotov zaradi enostavnosti dvodimenzionalnih problemskih paradigem [1]. V tridimenzionalnem svetu so problemi bolj zapleteni, kakor pri montažnem procesu, ki vključuje prepoznavanje tridimenzionalnega okolja in odločanje (krmiljenje) pri najmanj treh prostostnih stopnjah.

2 MONTAŽNI SISTEM KOT VEČDELNI ROBOTIZIRANI SISTEM

Zapletenost avtomatskega montažnega sistema je vsebovana že v pojmu montaža, ki pomeni gradnjo geometrijskih struktur. Zahteva zelo zahtevne gibalne in zaznavne zmožnosti in tudi določen intelektualni potencial za oblikovanje geometrijske oblike izdelka in karakteristike montažne strukture. Sam robot zadovolji le del teh zahtev. Enoročen in skoraj slep robot potrebuje pomoč dodatnih naprav ali drugih robotov za prenos, usmeritev, izbiro položaja in pritrjevanje. Vsi skupaj

control system that is expected to endow human-like and autonomous behavior to robots confronted with unknown problems. The questions that arise are as follows: how is it possible to build a knowledge base about something that is not known, and how then to teach a robot to cope with unknown problems? The only logical answer is that *the robot should be taught to learn on its own.*

1 AUTONOMOUS-BEHAVIOR-BASED ROBOTS

An autonomous robot means a working device with a certain motoric capability (motion and/or moving) that implements a generative planning system which interacts with a changing environment in real time. The given definition actually describes an intelligent agent with an embedded dynamic-reaction model based on belief-desire-intention architecture. It is usually called a "softbot", behavior-based robot or a decision-making "rational" being. In terms of automatic assembly, the autonomous agents should provide adaptation and planning methods as the answers to the nondeterministic dynamism of the working environment.

The complexity of the intellectual mechanism suggests that the aim of developing artificial intellectual models could be a fruitless or disappointing task. The magic of intelligence evolves in a long-term learning process. Our genetic legacy is dominant, particularly in the domain of learning [3]. But, it seems that learning models are more obvious, more understandable, since there is a chance to observe them in contrast to hidden, brain activities [2]. Hence, it is much more effective to build a learning system capable of designing the corresponding intellectual mechanism on its own. A system of this kind can be taught or trained, instead of being programmed, and reinforcement learning, neural networks and fuzzy logic are proven methods in intelligent robotics [7]. The most advanced results are achieved in the area of mobile robots, due to the simplicity of 2D-problem paradigms [1]. In the 3D world the problems can be more complicated; for example in the assembly process, which includes the recognition of 3D scenes and decision making (controlling) based on at least three degrees of freedom.

2 AN ASSEMBLY SYSTEM AS A MULTI-AGENT ROBOTIC SYSTEM

The complexity of an automatic assembly system comes from the complexity of the nature of the assembly, which comprises building geometrical structures. It requires very sophisticated motoric and perception capabilities, but also a certain intellectual potential to make conclusions about the geometry of the product and the characteristics of the assembly structure. The robot itself satisfies just a part of these requirements. Single-handed and nearly blind, the robot needs help based on complementary devices, or other robots, for sestavljajo urejen sistem. Določena sestavina je odgovorna za določeno nalogo in je določeno posebno mehanično bitje, odgovorno preostalim vključenim v montažni sistem. Pri vsakem od njih pričakujemo zmožnost odzivanja na spremembe, da prilagodi svojo geometrijsko obliko ali način delovanja. Če gledamo na montažni sistem tako, ga je mogoče razumeti kot nekakšen "socialni način delovanja" oziroma sistem, sestavljen iz sodelujočih posameznikov (članov). Vsak sistem več naprav oziroma vsak sistem, katerega delovanje je mogoče naravno razstaviti, je večdelni sistem. To pomeni, da lahko tudi en sam robot, krmiljen z več programi ali računalniki, ki drug z drugim sodelujejo, izkazuje zapleteno razumno obnašanje. Socialno obnašanje je najvišja oblika inteligence, ki lahko da mnoge prednosti v večdelnih robotskih sistemih. Te prednosti so:

- izboljšano delovanje sistema z uporabo vzporednosti pri zaznavanju;
- skupno odločanje, utemeljeno na porazdeljenem kriticizmu, prispeva h kreativnemu ustvarjanju idej, kako rešiti nov problem;
- zanesljivost, ki je posledica odvečnosti članov in zmanjšanje individualne kompleksnosti

3 MODEL SODELUJOČEGA VEČDELNEGA SISTEMA

Glavna parametra večdelnega sistema sta socialna organiziranost in komunikacija. Socialna organiziranost definira strukturo robotske družbe, ki določa sistemsko hierarhijo, odgovornosti članov in njihove vloge: vodje, sodelavce, nasprotnike pomočnike učitelje itn. Socialna organiziranost neposredno vpliva na obnašanje večdelnega sistema. Nekateri roboti bodo sodelovali in pomagali drug drugemu, nekateri bodo iskali druge poti, nekateri bodo skrbeli za varnost članov, nekateri bodo vzpodbujali združevanje ali pa težili k pokrivanju večjih delovnih področij. Razsodna funkcija bo ocenjevala obnašanje vsakega člena in napredek celotnega sistema. Ta pokaže, ali je določeno obnašanje imelo za posledico dobro delovanje in naj se pomni kot pozitivna izkušnja, ali opozori, če je obnašanje povzročilo neželene učinke.

Komuniciranje med členi je osnova članske družbe. Brez možnosti komunikacije členi ne morejo oblikovati družbe. Komunikacijski sistem mora definirati:

- kdaj komunicirati,
- kakšna je vsebina informacije,
- kdo je vključen v komunikacijo,
- kakšen je doseg komunikacije.

Komunikacija mora biti vzpostavljena na podlagi percepcije, vloge in trenutne pozicije/stanja. Na primer, nekaterim členom ni dovoljeno začeti komunikacije, ker niso voditelji ali odgovorni členi;

transport, orientation, positioning and fixturing. Altogether, they constitute a synchronized system. A particular component is responsible for a particular task, representing certain individual mechanicals being responsible to others combined in the assembly system. Each of them is expected to be able to respond to the change, or adapt their own geometry or course of action. Looking at the assembly system in this way, it can be interpreted as a kind of "social modus operandi" or a system built from collaborative individuals (agents). Any multi-device system or any system whose performance is naturally decomposable is a multi-agent system. This means that even one robot can be controlled by several programs or computers which, collaborating with each other, construct a complex intellectual behavior. Social behavior is the highest form of intelligence, which can provide many advantages in multi-agent robotic systems, such as:

- improved system performance by exploiting the parallelism of sensing and action,
- collective decision-making based on distributed criticism, contributing to the creative construction of ideas for solving new problems,
- reliability, which comes from agent redundancy and the reduction of individual complexity.

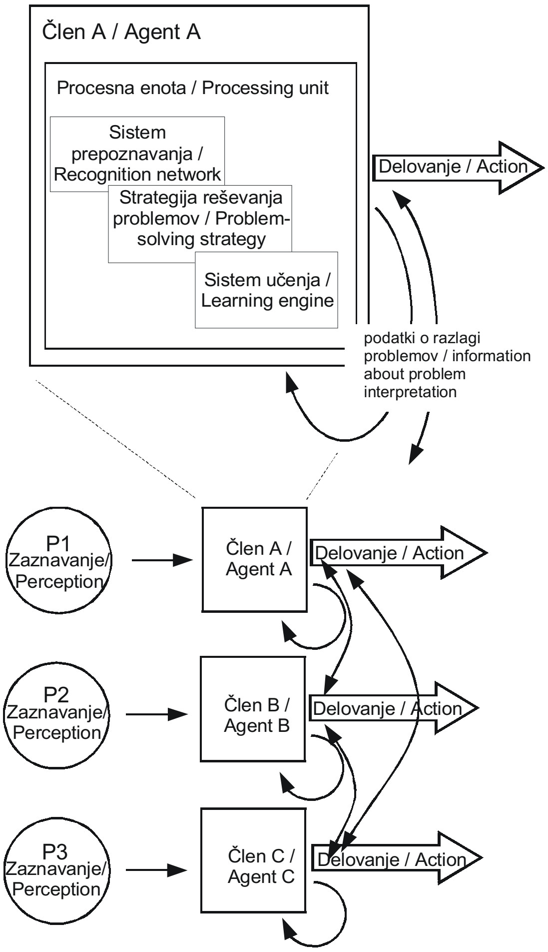
3 MODEL OF A COLLABORATIVE MULTI-AGENT SYSTEM

The main parameters of a multi-agent system are social organization and communication. The social organization defines the structure of a robotic society, which specifies the system hierarchy, the agent responsibilities and the roles – leaders, followers, opponents, helpers, teachers, etc. The social organization has direct effect on the behavior of the multi-agent system. Some of the agents will follow and help each other, some of them will look for other ways, some will take care of agent security, others will suggest congregation or will tend to cover a wider working area. The arbitration function evaluates the behavior of each agent and the progress of the whole system. It shows when some behavior has resulted in good actions, which should be learned as a positive experience, or alerts when bad behavior produces undesired effects.

The communication between agents is the basis of the agent community. Without the ability to communicate, the agents cannot create a community. The communication system must define:

- whether to communicate,
- what is the information content,
- who are the members in communication,
- what is the range of communication.

The communication should be established on the basis of perception, role and current position/ state. For example, some of the agents may not be allowed to initiate communication because they are not



Sl. 1. *Model sodelujočega večdelnega sistema*
Fig. 1. *The model of a collaborative multi-agent system*

nekateri členi so lahko zunaj komunikacijskega dosega, to pomeni da jim njihovo stanje ali položaj ne daje možnosti, da bi uspešno sodelovali pri reševanju dejanskega problema. Mnogostranost komunikacijskih pravil in njihovih kombinacij daje možnost ustvarjanja zelo zapletenega in ustvarjalnega socialnega obnašanja, kar ima za posledico zelo robusten stroj za reševanje problemov.

Slika 1 prikazuje model sodelujočega večdelnega sistema. Vsak člen ima procesno enoto, ki zajema sistem prepoznavanja, strategijo reševanja problemov in sistem učenja. Sistem prepoznavanja podobnih problemov, ki jih je mogoče rešiti s sedanjim znanjem, to je znanjem, zbranim iz izkušenj (primeri rešitev predhodnih problemov). Strategija reševanja problemov je vgrajeno preprosto splošno znanje, ki naj omogoča členu, da problem razišče in najde rešitev. To ni napreden in zahteven razumni mehanizem, ampak primitivni postopek preizkušanja: korak po korak dobro - slabo. Naloga sistema učenja je, da izboljša omenjeno preprosto strategijo reševanja problemov, tako da prilagaja znane postopke in/ali vključuje nove korake. Z ugotavljanjem uspešnosti delovanja jih sistem sprejme ali zavrne. Pozitivno delovanje se zapomni in oblikuje novo paradigmo

the leaders or responsible agents; some of the agents might be out of the communication range, i.e. their position or state does not give them a chance to be efficiently used for the solving of the encountered problem. The versatility of the communication rules and their combinations give us the opportunity to create very complex and creative multi-agent social behavior that can roll out the robust problem-solving engine.

The Figure 1 illustrates the model of a collaborative multiagent system. Each agent includes the processing unit, which combines the recognition network, the problem-solving strategy and the learning engine. The recognition engine is assumed to recognize similar problems that can be solved with existing knowledge, acquired on the basis of experience (previous problem-solving cases). The problem-solving strategy is the embedded, simple general knowledge, which should enable the agent to explore the problem and find the solution. This is not a sophisticated and intelligent mechanism, but rather a primitive, step-by-step, true-false procedure. The learning engine's aim is to improve the previously mentioned, simple problem-solving strategy, adapting the existing procedures and/or including new steps. By estimating the success of the actions the engine either accepts or rejects them. The positive actions are robotovega obnašanja. To bo predstavljalo model bodočega obnašanja člena v prihodnjih podobnih primerih.

Razlaga problemov in sklepi so skupek informacij za nadzor in komunikacijo. Podatki za nadzor so namenjeni za spodbujanje delovanja ali serijo delovanj, ki jih razpoznamo kot obnašanje. Informacija za sodelovanje je izvleček članove razlage problema. Te informacije se pošiljajo in/ali sprejemajo od drugih članov večdelnega sistema ali k njim. Informacija o sodelovanju vzpodbuja ali zavira funkcije, ki zvišujejo ali znižujejo motivacijo člena za določeno delo (pomagaj drugemu členu, vztrajaj pri trenutnem delu, spremeni ali ustavi akcijo itn.).

then recorded,and this forms the new paradigm of robot behavior that will represent the model of the agent's behavior in future, similar situations.

The problem's interpretation and conclusions represent the control and collaboration set of information. The control data are used to initiate an action, or the collection of actions, which can be recognized as a behavior. The collaboration information abstracts the agent's problem interpretation. They are transferred and/or received to/from the other members of the multi-agent system. The collaboration information serves as excitatory or inhibitory functions that rise or lower the motivation of the agent to undertake certain action (help another agent, persists in current work, changes or stops the action, etc.).

4 MODEL RAZUMNEGA ČLENA

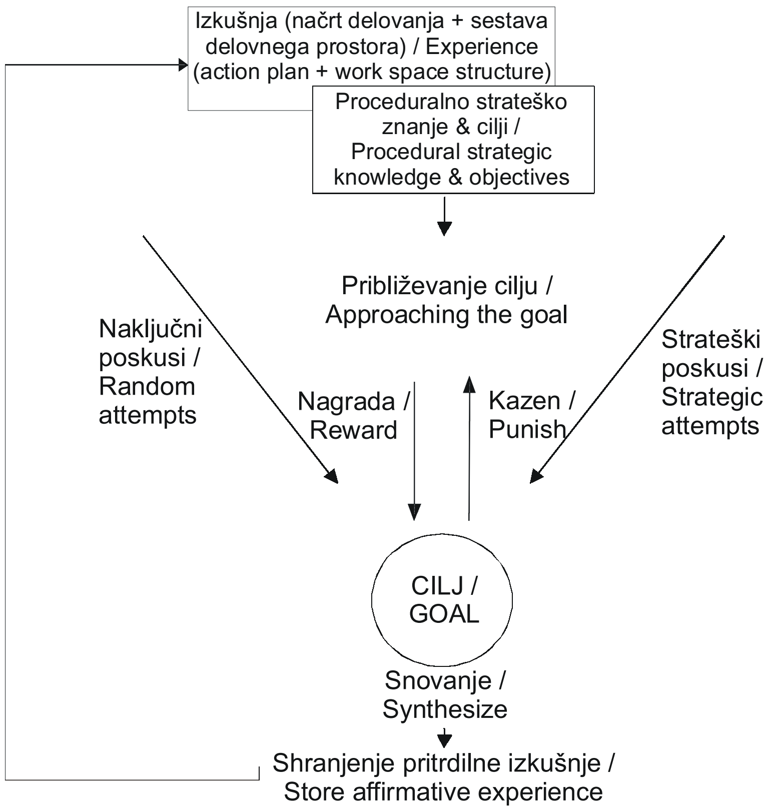
4.1 Sistem učenja

Sistem robotskega učenja mora zagotoviti zajemanje proceduralnega znanja, aktualna pravila za gibanje in postopke pa tudi učenje opisnega znanja o delovnem okolju in strukturah. Začetna predpostavka je, da robot ne ve ničesar. Je "tabula rasa" in ima le nekaj znanja glede določenih strateških splošnih postopkov za doseganje ciljev (prijeti sestavni del prek ovire, vstaviti neurejen del itn.) in o učnih metodah.

4 THE MODEL OF THE INTELLIGENT AGENT

4.1 Learning System

The robot learning system should enable the acquisition of procedural knowledge – actually, the moving action rules and procedures – as well as learning descriptive knowledge about the structures of the working environment. The starting assumption is that the robot does not know anything. It is a tabula rasa and has only some knowledge about certain strategic general procedures for attaining objectives – grasp work-piece over the obstacle, insert misaligned part and so on – and about the learning method.



Sl. 2. *Zasnova sistema robotskega učenja*
Fig. 2. *The concept of the robot learning system*

Slika 2 ponazarja predlagani sistem načrtovanja. Uporabljen je ojačan sistem učenja ([4] in [5]), ki temelji na strateških in naključnih poskusih. Postopek za ocenjevanje in iskanje napak konvergira k želenemu cilju tako, da kaznuje napačno delovanje in privzema uspešno. Ko se približa cilju, je treba zasnovati smiselne ukrepe in jih spraviti v spomin kot nekakšno izkušnjo, ki bo pomagala pri reševanju podobnih problemov v prihodnosti. Podobni problemi so tisti, ki so podobni glede na strukturo delovnega okolja. Ker zbrano znanje predstavljajo postopki, ki se nanašajo na ustrezne prostorske strukture, je robot zmožen delovati po postopkih, za katere je izurjen. Tako naj bi opravil nalogo z najmanjšim številom napak.

4.2 Sistem prepoznavanja

Naučeni celotni postopek naj se nanaša na pripadajoč prostorski načrt, ki je zajet s celotnim vizualnim sistemom. Z uporabo celotnega vida je robot zmožen prepoznati spremembe v delovnem prostoru, tako da primerja trenutno sliko z že znanimi paradigmami in se odloči o načinu obnašanja. V primeru podobnih struktur uporabi priučene postopke, v drugih nepoznanih ali bistveno različnih strukturah, mora začeti z iskanjem nove primerne poti.

Struktura delovnega prostora ne more biti zapisana kot simbolno kodiran zapis, ker bi to zahtevalo veliko računalniškega spomina za novo ali podobno situacijo. Za obdelavo tako obširne podatkovne baze bi bil potreben znaten čas. Model nevronskih mrež je uspešen način za obdelavo velikega števila vhodov in za njihoo zapomnjanje zgoščeno v obliki sinoptičnih uteži. Za uporabo pri reševanju strukturnih problemov morajo biti nevronske mreže zgrajene tako, da si lahko zapomnijo različne prostorske strukture in prepoznajo podobne. Izraz "podobna situacija" tukaj pomeni situacije, ki jih imamo običajno za podobne, na primer ovire, ki oblikujejo podobna prostorska razmerja, so malo premaknjene ali zasukane, ali pa se malo razlikujejo po obliki. Struktura delovnega prostora je predstavljena v obliki binarne matrike $n \times m$, ki predstavlja vstopni vektor mreže. Ničle pomenijo prazen prostor, enice pa diskretiziran prostor, kjer stoji ovira.

4.2.1 Prilagodljiva senčena mehka mreža (PSMM)

Za razpoznavanje prostorskih struktur po definiciji podobnosti je bila razvita PSM nevronska mreža. Postopek učenja razdeli v tri faze: začetek, učenje in delovanje.

V fazi začetka uporablja postopek iskanja težišča gruče (ITG) v izogib zlivanja različnih strukturnih kategorij, da zagotovi njihovo

Fig. 2. illustrates the proposed concept of the intelligent planning system. It implements the reinforcement learning ([4] and [5]) based on strategic and random attempts. The trial-and-error searching procedure converges on a given goal by punishing a wrong action or rewarding a successful one. After approaching the goal, reasonable actions should be synthesized and recorded as some kind of experience that will help solving similar problems in the future. Similar problems are those that resemble each other with regard to the structure of the work space. Since the gathered knowledge consists of procedures assigned to appropriate space structures, the robot is able to follow the trained procedure, expecting to accomplish the task with a minimum number of faults.

4.2 Recognition system

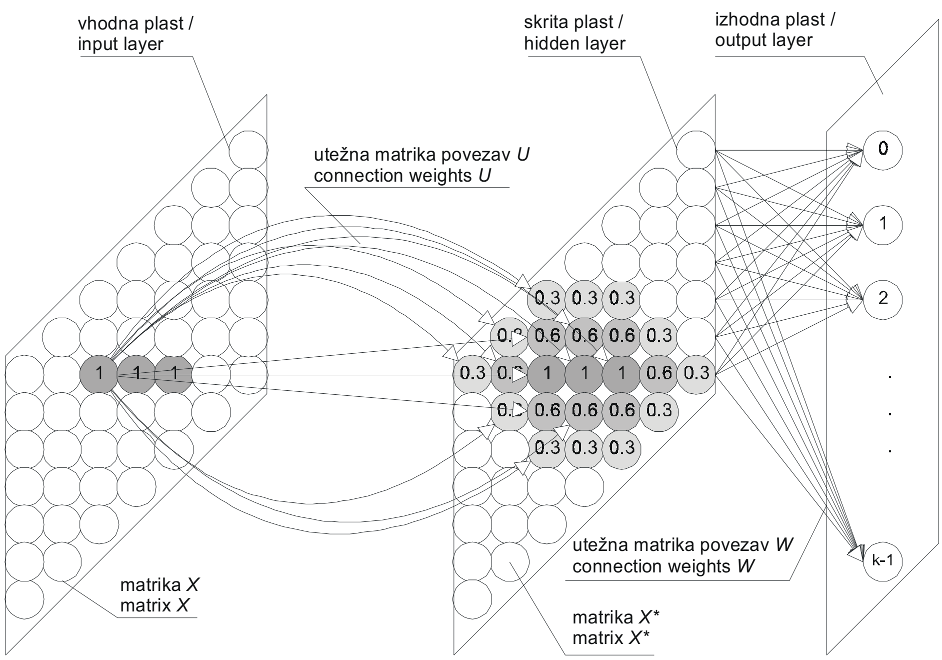
The learned moving procedure should be assigned to a corresponding work-space map acquired by the global vision system. Using the global view the robot is able to recognize changes in the structure of the work space, comparing the current space map with already experienced paradigms, and come to decisions about its behavior. In the cases of similar structures it uses learned procedures, in others, unknown or significantly different structures, it must undertake the searching of a new, appropriate path.

Work-space structure cannot be simply recorded as a symbolically coded description, because this would require a large computer memory for any new or similar situation encountered – and it would take a considerable time to search such a large database. The neural network model offers an efficient way to process a large number of input values and to memorize them, condensed as synaptic weights. Applied to the structural assignment problem, the neural network should be designed to memorize distinct work-space structures and to recognize similar ones. The term "similar situations" here denotes situations that are usually considered similar, i.e. situations where obstacles form similar spatial relations, slightly translated or rotated in any direction, or where they slightly differ in shape. The work-space structure is represented as a $n \times m$ binary matrix, which is assumed to be a network input vector. The zeros represent empty space and units denote the discrete space where the obstacle resides.

4.2.1 Adaptive fuzzy shadowed network

In order to provide recognition of work-space structures, according to the given definition of similarity, the Adaptive Fuzzy Shadowed (AFS) neural network has been designed. It divides the learning process into three phases: initiation, training and working.

In the initiation phase it uses the cluster center seeking approach (CCS) to prevent the blending of



Sl. 3. *Struktura adaptivne senčene mehke nevronske mreže*
Fig. 3. *Adaptive fuzzy shadowed network architecture*

uravnoteženo razporejanje in da bi izločil vpliv stopnje predstavitve problema. Algoritem ne sledi popolnoma algoritmu ITG, poznanemu pri [6]. Namesto računanja največje absolutne različnosti (ali najmanjše absolutne podobnosti), računa največjo relativno različnost (najmanjšo relativno podobnost) *Sp*. Vpliv velikosti ovire v razpoznavo težišča gruče je vključen, tako da upošteva raven ujemanja (število ujemajočih se enic) in velikost ovire (število enic). Vzorec težišča gruče tako predstavlja najbolj značilno strukturo primerkov, ki naj začne mrežo in ne omejuje števila izhodnih nevronov, ki bodo zajeti med učenjem, ki sledi.

Arhitektura mreže temelji na treh plasteh nevronov (sl.3 3). Namen skrite plasti je, da spremeni vhodni vektor *X,* da omogoči prepoznavanje bitno premaknjene ali zasukane situacije (v katerikoli smeri) kot podobno (vzbudi isti izhodni nevron). To je doseženo z dodajanjem sence okoli obrisa ovire. Intenzivnost sence se zmanjšuje z večanjam razdalje od ovire dva ali več ravni globoko, kakor to določa utežnostna funkcija senčenja (enačba 1) za vhodni vektor skrite plasti *X**.

distinct structure categories, to provide their balanced dissipation and to eliminate the influence of the order of the problem presentation. The algorithm does not completely follow the CCS algorithm known from [6]. Instead of calculating the maximum absolute dissimilarity (or minimum absolute similarity), the maximum relative dissimilarity (or minimum relative similarity) *Sp* is calculated. The influence of the size of the obstacle on the cluster center identification is thus included, considering the relation between the matching level (the number of matching "1's") and the obstacle size (the number of "1's"). The cluster center patterns actually represent the most distinctive structure samples that must initiate the network, and do not limit the final number of output neurons that will be acquired during the training that follows.

The network architecture is based on three neuron layers (Fig. 3.). The purpose of the hidden layer is to modify the input vector *X* in order to provide the recognition capability of bit-translated or rotated situations (in any direction) as similar situations (triggering the same output neuron). This is attained by adding shadows around the obstacle's contours. The shadow intensity decreases as the distance from the obstacle increases two or more levels deep as given by the shadowing weight function (Eq. 1) for a hidden-layer input vector *X**:

$$u_{iji^*j^*} = \begin{cases} 1 \;\forall\; (i^* = i \;\wedge\; j^* = j) \\ \alpha \cdot \dfrac{1}{|l_1| + |l_2|}; \quad \begin{array}{l} l_1 = |i^* - i| \\ l_2 = |j^* - j| \\ 0 < l_1 + l_2 \le l_{max} \end{array} \end{cases} \qquad (1),$$

kjer so:
$u_{iji^*j^*}$ - utežna funkcija med *ij* vhodnim nevronom in *i*j** nevronom skrite plasti,
α - koeficient linearnosti ($0 < \alpha < 1$)

where:
$u_{iji^*j^*}$ is the weight function between the *ij* input neuron and the *i*j** hidden-layer neuron,
α is the linearity coefficient ($0 < \alpha < 1$),

I_{max} - je velikost sence

Funkcija proženja in širjenja P_{i*j*} temelji na naslednjem pravilu

$$P_{i*j*} = \max_{ij}(x_{ij} u_{iji*j*}) \quad (2)$$

$$x^*_{i*j*} = P_{i*j*} \quad (3).$$

Tako je vhodna plast spremenjena iz binarnega v analogni vektor, kakor lahko vidimo na sliki 4. Vsak nevron v srednji plasti je povezan z vsakim nevronom v izhodni plasti. Ko je mreža začeta z različnimi strukturnimi primerki, sledi druga faza učenja trening, ki vključuje vse strukturne primerke. Stopnje, uporabljene v mrežnem algoritmu, so:

1. Začetek:
   β ($0 < \beta < 1$) parameter stopnje učenja,
   ρ ($0 < \rho < 1$) koeficient podobnosti,
   N = 0 število nevronov v izhodni plasti,
   C_{max} največje število težišč gruč.
2. Beri vse vhodne matrike X, ki jo sestavljajo binarni elementi
3. Najdi matriko z najmanjšo gostoto dn, ki bo prvo težišče gruče:

$$dn = \min_p \left\{ \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} x_{p_{ij}} \,,\, p = 0,1,..,(Np-1) \right\} \quad (4),$$

   kjer so: Np število vhodnih matrik, x_{pij} – ij element p-te vhodne matrike Xp, n – število vrstic v vhodni matriki, m – število stolpcev v vhodni matriki.
   Matrika X_d ($d \in \{0,1, \ldots, (Np-1)\}$) z najmanjšo gostoto dn postane matrika težišča prvega sklada $Y_1 = X_d$ ($C = 1$, C je število že znanih težišč).
4. Spremeni vhodne matrike z vključitvijo senc $X \rightarrow X^* = f(U)$, kjer je X vhodna binarna matrika, X^* je senčena analogna matrika.
5. Izračunaj relativno podobnost S_p med znanimi središči in preostalimi matrikami:

$$S_p = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \sum_{l=0}^{C} \left(x^*_{p_{ij}} \cdot y_{l_{ij}} \right)}{C \cdot \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} x^*_{p_{ij}}} \quad (5),$$

$$p = 0, 1, \ldots, (Np - 1);\; X^*_p \neq Y_l \forall l$$

   kjer je S_p podobnost p-te matrike z že znanimi središči, y_{lij} je ij-ti element od središča Y_l l-te matrike.
6. Najdi primerek z najmanjšo relativno podobnostjo S_{min} sedanjih središč:

$$S_{min} = \min_p \left\{ S_p, p = 0,1,\ldots,(Np - 1) \right\} \quad (6).$$

   Matrika X_j z najmanjšo relativno podobnostjo s sedanjimi težišča postane novo težišče $Y_C = X^*_p$ in število že znanih težišč postane: $C(t) = C(t-1) + 1$.
   Če je $C(t) < C_{max}$ pojdi nazaj na 5, sicer pojdi na 7.

I_{max} is the shadow size.

The propagation and activation function P_{i*j*} is based on the following rule:

In this way the input layer is transformed from a binary to an analogue vector, as can be seen in Fig. 4. Each neuron in the hidden layer is connected to every neuron in the output layer. After the network is initialized by the distinctive structure samples, the secondary learning-training phase follows, including all of the structure samples. The steps involved in the network algorithm are stated below:

1. Initialization:
   β ($0 < \beta < 1$) the learning rate parameter,
   ρ ($0 < \rho < 1$) the similarity coefficient,
   N = 0 the number of neurons in the output layer.
   C_{max} the maximum number of cluster centers.
2. Read all the input matrices X that consist of binary elements.
3. Find the matrix with the minimum density dn that will be the first cluster center:
   where Np is the number of input matrices, x_{pij} is the ij element of the p-th input matrix Xp, n is the number of rows in the input matrix, m is the number of columns in the input matrix.
   Matrix Xd ($d \in \{0, 1, \ldots, (Np-1)\}$), with the minimum density dn becomes the first cluster center matrix $Y_1 = X_d$ ($C = 1$, C is the number of already existing centers).
4. Transform the input matrix including the shadows $X \rightarrow X^* = f(U)$, where X is the input binary matrix, X^* is the shadowed analogue matrix.
5. Calculate the relative similarity S_p between the existing centers/center and the rest of the matrices:
   where S_p is the similarity of the p-th matrix with already existing centers, y_{lij} is the ij element of the l-th matrix center Y_p
6. Find exemplar with minimum relative similarity S_{min} to existing centers:
   The matrix Xp with minimum relative similarity to the existing centers becomes a new center $Y_C = X^*_p$ and the number of already existing centers becomes $C(t) = C(t-1) + 1$.
   If $C(t) < C_{max}$ then go back to 5, otherwise go to 7.

7. Začni mrežo z uporabo matrike težišča gruče $X = Y_l (l = 0, 1, ..., C_{max} - 1)$
   Če je $N = 0$ pojdi na 12, sicer pojdi na 9.
8. Uporabi naslednjo vhodno matriko $X = X_p (p = 0, 1, ..., Np - 1)$.
9. Izračunaj izbirno (podobnost) funkcijo T_k za vsak izhodni nevron:

7. Initialize the network by applying the cluster center matrix $X = Y_l (l = 0, 1, ..., C_{max} - 1)$
   if $N = 0$ then go to 12, otherwise go to 9.
8. Apply the next input matrix $X = X_p (p = 0, 1, ..., Np - 1)$.
9. Compute the choice (similarity) functions T_k for every output neuron:

$$T_k = \frac{\left\| X^* \wedge W_k \right\|}{\left\| X^* \vee W_k \right\|} \qquad (7),$$

$$k = 0, 1, ..., (N(t) - 1)$$

kjer so: $\wedge$ mehki "in" operator:
$(a \wedge b) = min\ (a,b)$,
$\vee$ mehki "ali" operator
$(a \vee b) = max\ (a, b)$,

where: $\wedge$ is the fuzzy "and" operator:
$(a \wedge b) = min\ (a,b)$,
$\vee$ is the fuzzy "or" operator
$(a \vee b) = max\ (a, b)$,

$$\left\| X^* \wedge W_k \right\| = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} min(x^*_{ij}, w_{k_{ij}}) \qquad (8)$$

$$\left\| X^* \vee W_k \right\| = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} max(x^*_{ij}, w_{k_{ij}}) \qquad (9).$$

10. Izberi primerek nevrona θ, ki se najbolje ujema – nevron v izhodni plasti z največjo vrednostjo izbirne (prožilne) funkcije:

10. Select the best matching examplar θ – the neuron in the output layer with the largest value of choice (activation) function:

$$T_\theta = \max_k \{ T_k \} \qquad (10).$$

11. Če je $T_k > \rho$, je zmagoviti nevron θ in pojdi na 13, če ne, nadaljuj z 12.
12. Oblikuj novi izhodni nevron (novi razred) θ, postavi število nevronov v izhodni plasti $N(t) = N(t-1) + 1$.
13. Prenovi mrežo za najbolj ujemajoči se primerek:
a) Če je nevron vzbujen prvič:

11. If $T_k > \rho$ the winner neuron is θ and go to 13, if not, continue with 12.
12. Create a new output neuron (a new class) θ. Set the number of neurons in the output layer $N(t) = N(t-1) + 1$.
13. Update the network for the best-matching examplar:
a) If the neuron is triggered for the first time:

$$W_\theta(t) = X^* \qquad (11)$$

W je utežna matrika povezav.
b) Če je nevron že bil vzbujen

W is the connection weight matrix.
b) If the neuron has already been triggered

$$w_{\theta_{ij}}(t) = w_{\theta_{ij}}(t-1) - \beta \cdot (w_{\theta_{ij}}(t-1) - x^*_{ij}) \qquad (12).$$

14. Če so bili uporabljena vsa težišča gruč $(l = C_{max} - 1)$, pojdi na 15, sicer na 7
15. Če so bile uporabljene vse vhodne matrike $(p = Np - 1)$ pojdi na 16, sicer na 8.
16. Konec.

14. If all the cluster centers are applied $(l = C_{max} - 1)$ go to 15, otherwise go to 7.
15. If all input matrices are applied $(p = Np - 1)$ go to 16, otherwise go to 8.
16. The end.

Če je bil izhodni nevron vzbujen prvič, se mreža prenovi za primerek, ki najbolj ustreza, enako kakor v ART1. Če je bil izhodni nevron že prej vzbujen, se mreža prenovi podbno kakor algoritem mehki ART. V mehki mreži ART se lahko uteži povezav samo zmanjšujejo ali ostanejo enake. V algoritmu PSMM pa se lahko uteži povezav padajo ali rastejo sorazmerno z razliko med vrednostmi matrike uteži povezav in spremenjeno vhodno matriko iz vmesne plasti. Parameter hitrosti učenja

If the output neuron is triggered for the first time, the network is updated for the best matching exemplar in the same manner as in ART1. If the output neuron has already been triggered, the network is updated in a similar way to the fuzzy ART algorithm. In the fuzzy ART network the connection weights can only decrease or remain the same. In the AFS algorithm the connection weights are decreased or increased in proportion to the difference between the values in the connection weight matrix and in the modified input matrix from the hidden layer. The

β določa, za koliko se lahko spremenijo uteži povezav v eni stopnji, to je, kako hitro se nevronska mreža uči.

PSMM s senčeno vmesno plastjo je zgrajena za stalno učenje, tudi v delovnem načinu. To je potrebno zaradi predpostavke, da se lahko vedno pojavijo nepredvidene prilike, ki niso bile zajete v fazi učenja. Učenje v delovnem načinu lahko povzroči kreacijo novih izhodnih nevronov (razredov), ali izboljšanje obstoječega znanja mreže.

5 SKLEPI

Razlaga robotskega montažnega sistema kot večdelnega sistema odpira nove poti pri gradnji razumnih in neodvisnih robotskih celic. Ta shema vsebuje zmožnost ustvarjanja sodelujočega sistema, ki lahko privede do doseganja socialne inteligence. Ima več prednosti: sistem UI je zgrajen iz preprostih razumov, ki jih je mogoče uspešno ustvariti, enostavni krmilni programi zagotavljajo robustnost sistema, mnogostranost komunukacijskih pravil daje možnost ustvarjanja zelo zapletenega in ustvarjalnega večdelnega delovnega obnašanja. Prikazan večdelni sistem vsebuje procesno enoto, ki kombinira enoto prepoznavanja, strategijo reševanja problemov in sistem učenja. Vključuje vse glavne pogoje: zaznavanje, prepoznavanje, reševanje problemov, učenje in komunikacijo. Sistem uporablja metodo učenja za iskanje novih rešitev in nevronsko mrežo za prepoznavanje strukturnih podobnosti v delovnem prostoru. Metoda iskanja omogoča reševanje nepoznanih problemov, z uporabo splošnih in naključnih postopkov, za podobne probleme pa uporablja zbrano znanje. Metoda učenja se uporablja za vrednotenje obnašanja robota in za ustvarjanje novega ali izboljševanje sedanjega znanja. Prilagodljiva senčena nevronska mehka mreža rabi kot robotov vizualni spomin, njena struktura je postavljena tako, da omogoča prepoznavanje zapletenih prostorskih struktur. Predstavljeni večdelni model rabi za osnovo računalniški simulaciji sodelujočega večdelnega sistema, ki bo kasneje testiran na resnični opremi.

learning-rate parameter β determines how much the connection weights are changed in one step, i.e. how fast the neural network learns.

The AFS network with a shadowed hidden layer is designed to learn all the time, even in the working mode. This is needed because the assumption is that unpredictable situations, which were not captured in the training phase, can occur. Learning in the working mode can induce the creation of new output neurons (classes), or the improvement of existing network knowledge.

5 CONCLUSION

The interpretation of a robotic assembly system as a multi-agent system opens a new way of designing intelligent and autonomous robotic cells. Such a scheme comprises the ability to create a collaborative system that can achieve social intelligence. It has several advantages: the AI system is built from simple intellects, which can be efficiently created; simple control programs ensure the robustness of the whole system; the versatility of the communication rules and their combinations give the opportunity to create very complex and creative multi-agent working behavior. The presented multi-agent model comprises the processing unit, which combines the recognition network, the problem-solving strategy and the learning engine. It integrates the main prerequisites: perception, recognition, problem solving, learning and communication. The system employs the reinforcement learning method for acquiring new solutions and a neural network for the recognition of work-space structure similarity. The searching method enables the solving of unknown problems, following general and random procedures, as well as similar problems, using acquired knowledge. The reinforcement learning method is used to evaluate robot behavior and to induce new, or to improve the existing, knowledge. The Adaptive Fuzzy Shadowed neural network is designed to serve as a robot visual memory, and its architecture is realized in order to contribute to the recognition of complex spatial structures. The presented multi-agent model serves as the basis for building a computer simulation of a collaborative multiagent system, which can afterwards be tested on real equipment.

6 LITERATURA
6 REFERENCES

[1] Bergman, R. (1995) Learning world models in environments with manifest causal structure, Massachusetts Institute of Technology, *AI Technical Report 1513*.

[2] Canamero, D. (1996) Modeling motivations and emotions as a basis for intelligent behavior, Massachusetts Institute of Technology, *AI memo 1597*.

[3] Jerbić B., K.Grolinger, and B. Vranješ B. (1999) Autonomous agent based on reinforcement learning and adaptive shadowed network, *Artificial Intelligence in Engineering*, Vol. 13, No. 2, 141-157.

[4] Koenig, S. and R.G. Simmons (1992) Complexity analysis of real-time reinforcement learning applied to finding shortest paths in deterministic domains, *Technical Report CMU-CS-93-106,* School of Computer Science, Carnegie Mellon University, 1992.
[5] Mahadevan, S. and J. Connell (1992) Automatic programming of behavior-based robots using reinforcement learning, *Artificial Intelligence*, 55, 311-365.
[6] Rao, H.A. and P. Gu (1995) A multi-constraint network for the pragmatic design of cellular manufacturing system*, International Journal of Production Research*, 33, n. 4, 1049-1070.
[7] Sutton, R.S. and A.G. Barto (1998*)* Reinforcement learning, *A Bradford Book*, ISBN 0-262-19398-1, London.

Naslov avtorjev: prof.dr. Bojan Jerbić
prof.dr. Božo Vranješ
University of Zagreb
Faculty of Mechanical Eng. and
Naval Architecture
I. Lučića 5
10000 Zagreb, Croatia
bojan.jerbic@fsb.hr
bozo.vranjes@fsb.hr

Authors' Address: Prof.Dr. Bojan Jerbić
Prof.Dr. Božo Vranješ
University of Zagreb
Faculty of Mechanical Eng.
and Naval Architecture
I. Lučića 5
10000 Zagreb, Croatia
bojan.jerbic@fsb.hr
bozo.vranjes@fsb.hr

Prejeto:
Received: 15.3.2001

Sprejeto:
Accepted: 29.5.2003

Odprt za diskusijo: 1 leto
Open for discussion: 1 year