Proceedings of the World Congress on Engineering 2010 Vol I
WCE 2010, June 30 - July 2, 2010, London, U.K.

Path Planning for Robot Navigation using View Sequences

Mateus Mendes*†, A. Paulo Coimbra*, and Manuel M. Crisóstomo *

Abstract—**Navigation based on visual memories is very common among humans. However, planning long trips requires also a more sophisticated representation of the environment, such as a topological map. This paper describes a system that learns paths by storing sequences of images and image information in a Sparse Distributed Memory. Connections between paths are detected by exploring similarities in the images, and a topological representation of the connections is created. The robot is then able to plan paths and skip from one path to another at the connection points. The system was tested under reconstitutions of country and urban environments, and it was able to successfully plan paths and navigate.**

Keywords: SDM, Sparse Distributed Memory, Robot Navigation, Path Planning

1 Introduction

About 80 % of all the information humans rely on is visual [1], and the brain operates mostly with sequences of images [2]. View sequence based navigation is also extremely attractive for autonomous robots, for the hardware is very straightforward, and the approach is biologically plausible. However, while humans are able to navigate quite well based only on visual information, images usually require huge computer processing power. This means that for real time robot operation, visual information is often avoided. Other sensors, such as sonar or laser range finders provide accurate information at a much lower computational cost.

The goal of equipping robots with cameras and vision-based navigation is still an open research issue. The use of special landmarks (possibly artificial, such as barcodes or data matrices), is a trick that can greatly improve the accuracy of the system [3]. As for the images, there are two popular approaches: one that uses plain images [4], the other that uses panoramic images [5]. Panoramic images offer a 360° view, which is richer than a plain front or rear view. However, this richness comes at the cost of even additional processing power requirements. Some authors have also proposed techniques to speed up processing and/or reduce memory needs. Matsumoto [6] uses images as small as 32x32 pixels. Ishiguro [7] replaced the images by their Fourier transforms. Winters [8] compresses the images using Principal Component Analysis.

The images alone are a means for instantaneous localisation. View-based navigation is almost always based on the same idea: during a learning stage the robot learns a sequence of views and motor commands that, if followed with minimum drift, will lead it to a target location. By following the sequence of commands, possibly correcting the small drifts that may occur, the robot is later able to follow the learnt path. This idea is very simple and it works for single paths. However, for more complex trips, path planning is necessary. To plan paths, skipping from one to another when necessary, more sophisticated representations of the environment are required. Namely, metric or topological maps can be used [9]. Those maps represent paths and connections between them, making it possible to use algorithms such as A* for intelligent navigation.

This paper explains how view-based navigation is achieved using a Sparse Distributed Memory (SDM) to store sequences of images. The memory is also used to recognise overlaps of the paths and thus establish connection nodes where the robot can skip from one path to another. This way, a topological representation of the world can be constructed, and the system can plan paths. Section 2 explains navigation based on view sequences in more detail. Section 3 explains how the SDM works. In Section 4 the robot used is described. Section 5 describes the navigation algorithm, and Section 6 shows and discusses the results obtained.

2 Navigation using view sequences

Usually, the view-based approaches for robot navigation are based on the concept of a “view-sequence” and a look-up table of motor commands. In the present work, the approach is very close to that of Matsumoto et al. [6]. This approach requires a learning stage, during which the robot must be manually guided. While being guided, the robot memorises a sequence of views automatically. While autonomously running, the robot performs automatic image based localisation and obstacle detection, taking action in real-time.

*ISR - Institute of Systems and Robotics, Dept. of Electrical and Computer Engineering, University of Coimbra, Portugal. E-mail: acoimbra@deec.uc.pt, mcris@isr.uc.pt. †ESTGOH, Polytechnic Institute of Coimbra, Portugal. E-mail: mmendes@estgoh.ipc.pt.

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

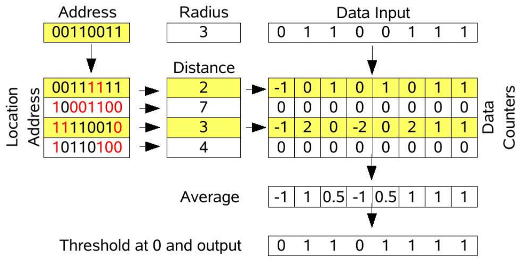


Figure 1: One model of a SDM, using bit counters.

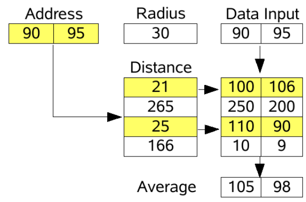


Figure 2: Alternative architecture of the SDM, auto-associative and using integers.

Localisation is estimated based on the similarity of two views: one stored during the learning stage and another grabbed in real-time. The robot tries to find matching areas between those two images, and calculates the horizontal distance between them in order to infer *how far* it is from the correct path. That distance is then used to correct eventual drifts to the left or to the right. This technique is described in more detail in [10].

3 Sparse Distributed Memories

The Sparse Distributed Memory is an associative memory model proposed by Kanerva in the 1980s [2]. It is suitable to work with high dimensional binary vectors. In this case, an image can be regarded as a high dimensional vector, and the SDM can be used simultaneously as a sophisticated storage and retrieval mechanism and a pattern recognition tool.

3.1 The original model

The underlying idea behind the SDM is the mapping of a huge binary memory onto a smaller set of physical locations, called *hard locations*. As a general guideline, those hard locations should be uniformely distributed in the virtual space, to *mimic* the existence of the larger virtual space as accurately as possible. Every datum is stored by distribution to a set of hard locations, and retrieved by *averaging* those locations and comparing the result to a given threshold. Figure 1 shows a model of a SDM. "Address" is the reference address where the datum is to be stored or read from. It will activate all the hard locations within a given access radius, which is predefined. Kanerva proposes that the Hamming distance, that is the number of bits in which two binary vectors are different, be used as the measure of distance between the addresses. All the locations that differ less than a predefined number of bits from the input address are selected for the read or write operation.

Data are stored in arrays of counters, one counter for every bit of every location. Writing is done by incrementing or decrementing the bit counters at the selected addresses. To store 0 at a given position, the corresponding counter is decremented. To store 1, it is incremented. Reading is done by averaging the values of all the counters columnwise and thresholding at a predefined value. If the value of the sum is below the threshold, the bit is zero, otherwise it is one.

Initially, all the bit counters must be set to zero, for the memory stores no data. The bits of the address locations should be set randomly, so that the addresses would be uniformely distributed in the addressing space. There's no guarantee that the data retrieved is exactly the same that was written. It should be, providing that the hard locations are correctly distributed over the binary space and the memory has not reached saturation.

3.2 The model used

The original SDM model, though theoretically sound and attractive, has some faults. One problem is that of selecting the hard locations at random in the beginning of the operation. Another problem is that of using bit counters, which cause a very low storage rate of about 0.1 bits per bit of traditional computer memory and slow down the system. These problems have been thoroughly described in [11], where the authors study alternative architectures and methods of encoding the data.

To overcome the problem of placing hard locations in the address space, in this work the hard locations are selected using the Randomised Reallocation algorithm [12]. The idea is that the system starts with an empty memory and allocates new hard locations when there's a new datum which cannot be stored in enough existing locations. The new locations are placed *randomly* in the neighbourhood of the new datum address. To overcome the problem of using bit counters, the bits are grouped as integers, as shown in Figure 2. Addressing is done using an arithmetic distance, instead of the Hamming distance. Learning is achieved updating each byte value using the equation:

$$h_t^k = h_{t-1}^k + \alpha \cdot (x^k - h_{t-1}^k), \quad \alpha \in \mathbb{R} \wedge 0 \le \alpha \le 1 \quad (1)$$

h_t^k is the k^{th} number of the hard location, at time t. x^k is the corresponding number in the input vector x. α is the learning rate—in this case it was set to 1, enforcing one shot learning.

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

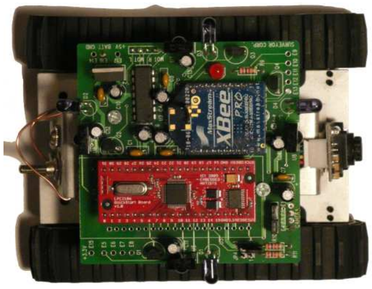


Figure 3: Robot used.

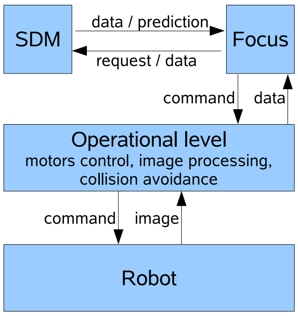


Figure 4: Architecture of the implemented software.

4 Experimental Platform

The robot used was a Surveyor[1] SRV-1, a small robot with tank-style treads and differential drive via two precision DC gearmotors (Figure 3). Among other features, it has a built in digital video camera and a 802.15.4 radio communication module. This robot was controlled in real time from a laptop with a 1.8 GHz processor and 1 Gb RAM. The overall software architecture is as shown in Figure 4. It contains three basic modules:

1. The SDM, where the information is stored.
2. The Focus (following Kanerva's terminology), where the navigation algorithms are run.
3. An operational layer, responsible for interfacing the hardware and some tasks such as motor control, collision avoidance and image equalisation.

Navigation is based on vision, and has two modes: supervised learning, in which the robot is manually guided and captures images to store for future reference; and autonomous running, in which it uses previous knowledge to navigate autonomously, following any sequence previously learnt. The vectors stored in the SDM consist of arrays of bytes, as summarised in Equation 2:

$$x_i = < im_i, seq\_id, i, timestamp, motion > \quad (2)$$

[1]http://www.surveyor.com.

In the vector, im_i is the image i, in PGM (Portable Gray Map) format and 80×64 resolution. In PGM images, every pixel is represented by an 8-bit integer. 0 is black, 255 is white. seq_id is an auto-incremented, 4-byte integer, unique for each sequence. It is used to identify which sequence the vector belongs to. i is an auto-incremented, 4-byte integer, unique for every vector in the sequence, used to quickly identify every image in the sequence. $timestamp$ is a 4-byte integer, storing Unix timestamp. It is not being used so far for navigation purposes. $motion$ is a single character, identifying the type of movement the robot performed after the image was grabbed.

The image alone uses 5120 bytes. The overhead information comprises 13 additional bytes. Hence, the input vector contains 5133 bytes.

5 Mapping and planning

The "teach and follow" approach *per si* is very simple and powerful. But for robust navigation and route planning, it is necessary to extend the basic algorithm to perform tasks such as detection of connection points between the paths learnt and disambiguation when there are similar images or divergent paths.

5.1 Filtering out unnecessary images

During learning in vision-based navigation, not every single picture has to be stored. There are scenarios, such as corridors, in which the views are very similar for a long period of time. Those images do not provide data useful for navigation. Therefore, they can be filtered out during the learning stage, so that only images which are *sufficiently* different from their predecessors must be stored. This behaviour can be easily implemented using the SDM: every new image is only stored if there is no image within a predefined radius in the SDM. If the error is below a given threshold, the new image is discarded. A good threshold for this purpose is the memory activation radius. New images that are less than an activation radius from an already stored image will be stored in the same hard locations. They are most probably unnecessary.

5.2 Detecting connection points

Another situation in which new images don't provide useful information is the case when two paths have a common segment, such as depicted in Figure 5. The figure shows two different paths, 1 and 2, in which the segment AB is common. If the robot learns segment AB for path 1, for example, then it does not need to learn it again for segment 2. When learning path number 2, it only needs to learn it until point A. Then it can store an association between paths 1 and 2 at point A and skip all the images until point B. At point B, it should again record a connection between paths 1 and 2. This way, it builds a map of

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

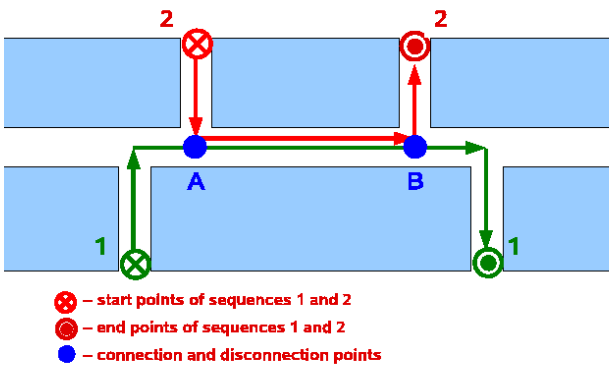


Figure 5: Example of paths that have a common segment. The robot only needs to learn AB once.

the connection points between the known paths. This is a kind of topological representation of the environment.

The main problem with this approach is to detect the connection points. The points where the paths come together (point A in Figure 5) can be detected after a *reasonable* number of images of path 1 have been retrieved, when the robot is learning path 2. When that happens, the robot stores the connection in its working memory and stops learning path 2. From that point onwards, it keeps monitoring if it is following the same path that it has learnt. After a *reasonable* number of predictions have failed, it adds another connection point to the graph and resumes learning the new path. In the tests with the SDM, a number of 3–5 consecutive images within the access radius usually sufficed to establish a connection point, and 3–5 images out of the access radius was a good indicator that the paths were diverging again.

5.3 Sequence Disambiguation

One problem that arises when using navigation based on sequences is that of sequence disambiguation. Under normal circumstances, it is possible the occurrence of sequences such as 1) ABC; 2) XBZ; or 3) DEFEG, each letter representing a random input vector. There are two different problems with these three sequences: 1) and 2) both share one common element (B); and one element (E) occurs in two different positions of sequence 3). In the first case, the successor of B can be either C or Z. In the second case, the successor of E can be either F or G. The correct prediction depends on the history of the system. One possible solution relies on using a kind of *short term* memory.

Kanerva proposes a solution in which the input to the SDM is not the last input D_t, but the juxtaposition of the last k inputs $\{D_t, D_{t-1}...D_{t-k}\}$. This technique is called $folding$, and k is the number of $folds$. The disadvantage is that it greatly increases the dimensionality of the input vector. J. Bose [13] uses an additional neural network, to store a measure of the *context*, instead of adding folds to the memory.

In the present work, it seemed more appropriate a solution inspired by Jaeckel and Karlsson's proposal of segmenting the addressing space [14]. Jaeckel and Karlsson propose to fix a certain number of coordinates when addressing, thus reducing the number of hard locations that can be selected. In the present work, the goal is to retrieve an image just within the sequence that is being followed. Hence, this idea can be applied here. The number of the sequence can be *fixed*, thus truncating the addressing space.

6 Tests and Results

For practical constraints, the tests were performed in a small testbed in the laboratory. This testbed consisted of an arena surrounded by a realistic countryside scenario, or filled with objects simulating a urban environment.

6.1 Tests in an open arena simulating a country environment

The first test performed consisted in analysing the behaviour of the navigation algorithm in the open arena. The surrounding wall was printed with a composition of images of mountain views, as shown in Figure 8. The field of view of the camera is relatively narrow (about 40°), so the robot cannot capture above or beyond the wall. Sometimes it can capture parts of the floor.

Figure 6 shows an example of the results obtained. In the example, the robot was first taught paths L1 and L2. Then the memory was loaded with both sequences, establishing connection points A and B. The minimum *overlapping* images required for establishing a connection point was set to 3 consecutive images. The minimum number of different images necessary for splitting the paths at point B was also set to 3 consecutive images out of the access radius. The lines in Figure 6 were drawn by a pen attached to the rear of the robot. Therefore, they represent the motion of the rear, not the centre of the robot, causing the arcs that appear when the robot changes direction. As the picture shows, the robot was able to start at the beginning of sequence L1 and finish at the end of sequence L2, and vice-versa. Regardless of its starting point, at point A it always defaulted to the only known path L1. This explains the small arc that appears at point A in path F2. This arc represents an adjustment of the heading when the robot defaulted to path L1.

The direction the robot takes at point B depends on its goal. If the goal is to follow path L1, it continues along that path. If the goal is to follow path L2, it will disambiguate the predictions to retrieve only images from path L2. This behaviour explains the changes in direction that appear in the red line (F1) at point B. The arcs were drawn when the robot started at path L1, but with

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

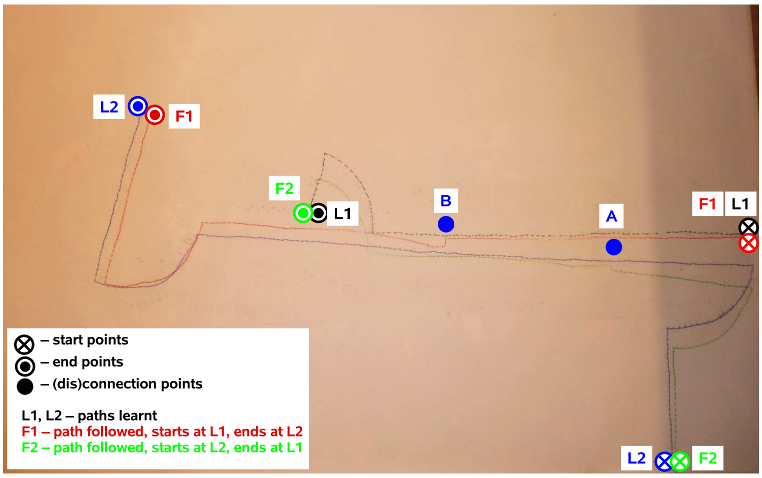


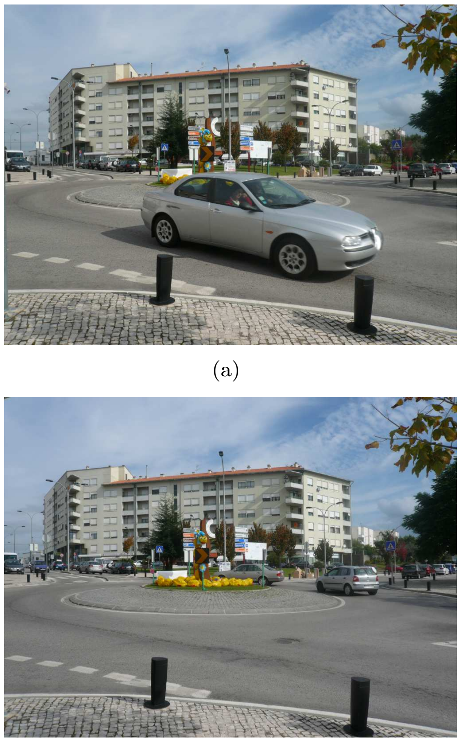
Figure 6: Results: paths taught and followed. The robot successfully skips from one path to another and node points A and B.

the goal of reaching the end of path L2.

6.2 Tests in a simulated urban environment

In a second experiment, the scenario was filled with images mimicking a typical city environment. Urban environments change very often. Ideally, the robot should learn one path in a urban environment but still be able to follow it in case there are small changes, up to an *acceptable* level. For example, Figure 7 shows two pictures of a traffic turn, taken only a few seconds one after the other. Although the remaining scenario holds, one picture captures only the back of a car in background. The other picture captures a side view of another car in foreground.

Due to the small dimensions of the robot, it was not tested in a real city environment, but in a reconstruction of it. Figure 8 shows the results. Figure 8(a) shows the first scenario, where the robot was taught. In this scenario the robot, during segment AB, is guided essentially by the image of the traffic turn without the car. In a second part of this experiment the picture of the traffic turn was replaced by the one with the car in foreground, and the robot was made to follow the same paths. Again, it had to start at path L1 and finish at path L2, and vice-versa. As Figure 8(b) shows, it was able to successfully complete the tasks.



(a)

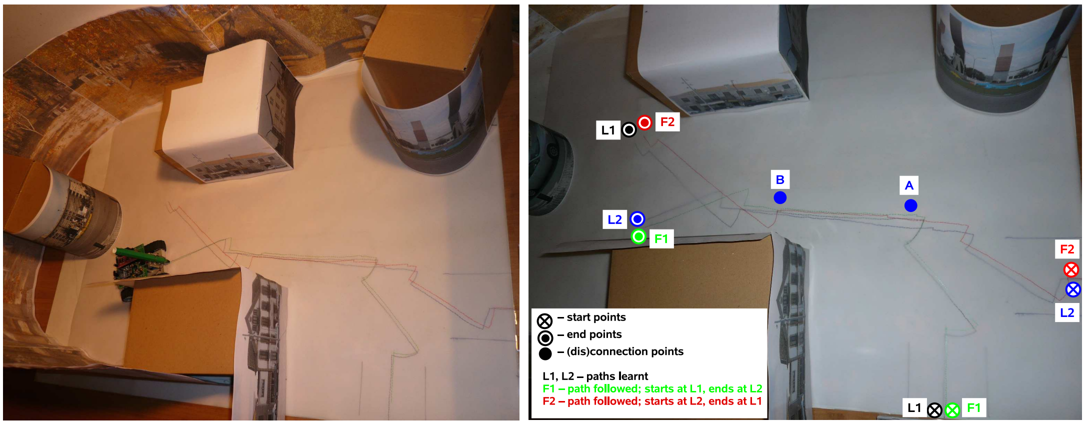
(b)

Figure 7: Typical city view, where the traffic turn is temporarily occluded by passing cars.

7 Conclusions and future work

Navigation based on view sequences is still an open research question. In this paper, a novel method was proposed that can provide view-based navigation based on a SDM. During a learning stage, the robot learns new paths. Connection points are established when two paths come together or split. This way, a topological representation of the space is built, which confers on the robot the ability to skip from one sequence to another and plan

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)



(a) (b)

Figure 8: Paths learnt (blue and black) and followed, with small scenario changes. The robot plans correctly the routes and is immune to small changes in the reconstituted urban scenario.

new paths. One drawback of this approach is that the SDM model, simulated in software as in this case, requires a lot of processing and is very slow to operate in real time. Another disadvantage is that using front views the robot only merges paths that come together in the same heading.

The results shown prove the feasibility of the approach. The robot was tested in two different environments, one that is a reconstitution of a country environment, the other a reconstitution of a changing urban environment. It was able to complete the tasks, even under changing conditions.

References

[1] Steven Johnson. *Mind wide open.* Scribner, New York, 2004.

[2] Pentti Kanerva. *Sparse Distributed Memory.* MIT Press, Cambridge, 1988.

[3] Christopher Rasmussen and Gregory D. Hager. Robot navigation using image sequences. In *In Proc. AAAI*, pages 938–943, 1996.

[4] Yoshio Matsumoto, Kazunori Ikeda, Masayuki Inaba, and Hirochika Inoue. Exploration and map acquisition for view-based navigation in corridor environment. In *Proc. of the Int. Conference on Field and Service Robotics*, pages 341–346, 1999.

[5] Yoshio Matsumoto, Masayuki Inaba, and Hirochika Inoue. View-based navigation using an omniview sequence in a corridor environment. In *Machine Vision and Applications*, 2003.

[6] Yoshio Matsumoto, Masayuki Inaba, and Hirochika Inoue. View-based approach to robot navigation. In *Proc. of 2000 IEEE/RSJ Int. Conference on Intelligent Robots and Systems (IROS 2000)*, 2000.

[7] Hiroshi Ishiguro and Saburo Tsuji. Image-based memory of environment. In *in Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, 1996.

[8] Niall Winters and José Santos-Victor. Mobile robot navigation using omni-directional vision. In *In Proc. 3rd Irish Machine Vision and Image Processing Conference (IMVIP'99)*, pages 151–166, 1999.

[9] J. Meyer. Map-based navigation in mobile robots: Ii. a review of map-learning and path-planning strategies. *Cognitive Systems Research*, 4(4):283–317, December 2003.

[10] Mateus Mendes, Manuel M. Crisóstomo, and A. Paulo Coimbra. Robot navigation using a sparse distributed memory. In *Proceedings of the 2008 IEEE International Conference on Robotics and Automation*, Pasadena, California, USA, May 2008.

[11] Mateus Mendes, Manuel M. Crisóstomo, and A. Paulo Coimbra. Assessing a sparse distributed memory using different encoding methods. In *Proc. of the 2009 Int. Conference of Computational Intelligence and Intelligent Systems*, London, UK, July 2009.

[12] Bohdana Ratitch and Doina Precup. Sparse distributed memories for on-line value-based reinforcement learning. In *ECML*, 2004.

[13] Joy Bose. A scalable sparse distributed neural memory model. Master's thesis, University of Manchester, Faculty of Science and Engineering, Manchester, UK, 2003.

[14] Louis A. Jaeckel. An alternative design for a sparse distributed memory. Technical report, Research Institute for Advanced Computer Science, NASA Ames Research Center, July 1989.

ISBN: 978-988-17012-9-9
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)