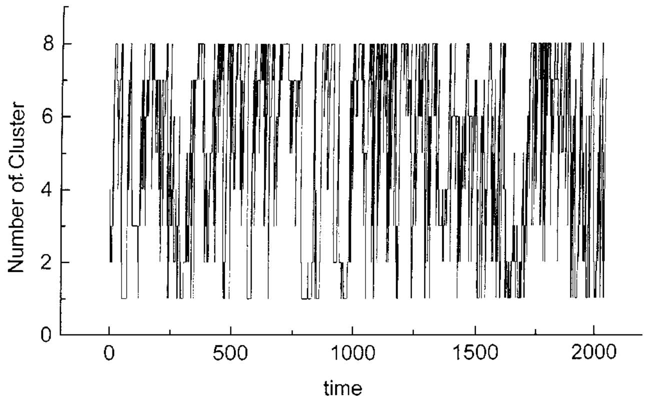

Fig. 11. Time series of the number of clusters N_c for the case of $\alpha = 0.296$, $M = 80.0$ krad/s, and $\Delta f = 1.0$ kHz.

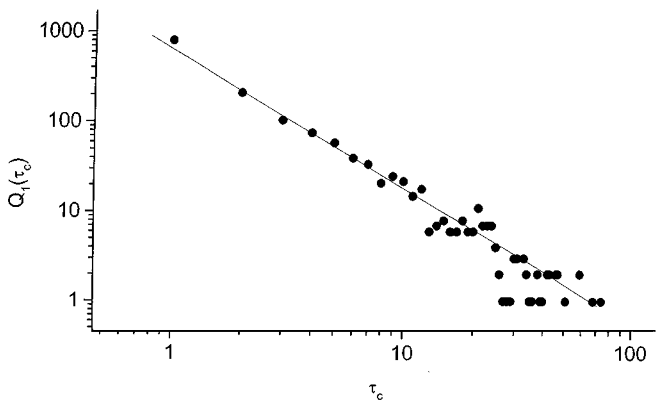

Fig. 12. Distribution function $Q_1(\tau_c)$ of the residence time τ_c for the state of $N_c = 1$. A straight line is drawn by the least squares method and the value of slope is -1.54.

The cooperative phenomena in the globally coupled system have been mainly studied in the map system. The present experimental system can sufficiently show such dynamical behaviors studied in the map system even though the system size is very small.

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Analysis of Practical Expectation of the Capacity of PBHC with Fault Tolerance

Chua-Chin Wang and Cheng-Fa Tsai

***Abstract*—This investigation presents a novel method of practical expectation of the capacity of polynomial bidirectional heterocorrelator (PBHC). This has a higher capacity for pattern pair storage than that of the conventional bidirectional associative memories and fuzzy memories. In this brief, the practical capacity of the data processing using PBHC considering fault tolerance in the average case is estimated, simulation results are presented to verify the derived theory.**

***Index Terms*—Associative memory, fuzzy data, neural networks.**

I. INTRODUCTION

Associative memories have received comprehensive interest in neural networks [1], [2]. The bidirectional associative memory-like (BAM-like) associative memory is a two-layer heteroassociator that stores a set of bipolar pairs. Owing to their easiness to be encoded and high noise immunity, BAMs are suitable for pattern recognition, intelligent control, and optimization problems. The original Kosko's BAM suffers from low storage capacity [2]. Thus, many efforts have been made to improve the performance of Kosko's BAM [3]–[5]. Some of these models strengthen the BAM architecture by using the Hamming stability learning algorithm (SBAM) [3], the asymmetrical BAM model (ABAM) [4], or introducing a general model of BAM (GBAM) to improve the performance [5]. The capacity of GBAM is claimed to exceed all the above BAMs [5].

Kosko's fuzzy associative memory (FAM) is the very first example to use neural networks to articulate fuzzy rules for fuzzy systems [6]. Despite its simplicity and modularity, his model suffers from extremely low memory capacity, i.e., one rule per FAM matrix. Besides, it is limited to small rule-based applications. There has been a renewal of interest in fuzzy associative memories in recent years. For instance, Yamaguchi [7] presented a method to represent fuzzy IF-THEN rules using associative memories and carry out fuzzy inference using association; a conceptual fuzzy set (CFS) comprised of distributed fuzzy knowledge processing have been proposed by Takagi [8]. However, it is difficult to apply FAM to complex knowledge processing, because associative memories have very poor storage capacity. Chung and Lee [9] proposed a multiple-rule storage method of a FAM matrix. They showed that more than one rule can be encoded by Kosko's FAM. However, the actual capacity will depend on the dimension of the matrix and the rule characteristics, e.g., how many the rules are overlapped. The capacity of this model depends on whether the membership function is semioverlapped or not.

In this brief, we present a novel method of data processing using polynomial bidirectional heterocorrelator (PBHC). A perfect recall theorem is established and the implementation of the PBHC model is more efficient accordingly. This has a higher capacity for pattern pair storage than that of the conventional BAMs and fuzzy memories. The PBHC takes advantage of fuzzy characteristics in evolution equations such that the signal–noise ratio (SNR) of data recall is significantly in-

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creased. Furthermore, we utilize a two-phase approach to demonstrate the stability of fuzzy PBHC. Finally, the practical expectation value of the capacity of the PBHC with fault tolerance in the average case is estimated.

II. Framework of High Capacity PBHC

A. Evolution Equations

Assume that we are given M pattern pairs, which are $\{(X_1, Y_1), (X_2, Y_2), \cdots, (X_M, Y_M)\}$, where $X_i = x_{i1}, x_{i2}, \cdots, x_{in}$), $Y_i = (y_{i1}, y_{i2}, \cdots, y_{ip})$. Let $1 \le i \le M$, $x_{ij} \in [0,1]$, $1 \le j \le n$, $y_{ij} \in [0,1]$, $1 \le j \le p$, n and p are the component dimensions of X_i and Y_i, and n is assumed to be smaller than or equal to p without any loss of generality. $x_{ij}, y_{ij} \in \{0/\lambda, 1/\lambda, \cdots, \lambda/\lambda\}$, fuzzy space = [1, 0], λ is a fuzzy quantum, and σ is a fuzzy quantum gap. Instead of using Kosko's approach, we use the following evolution equations in the recall process of the PBHC

$$y_k = H\left(\frac{\sum_{i=1}^{M} y_{ik} \cdot ((u - \|X_i - X\|^2)/u)^{M^Z}}{\sum_{i=1}^{M} ((u - \|X_i - X\|^2)/u)^{M^Z}}\right)$$

$$x_k = H\left(\frac{\sum_{i=1}^{M} x_{ik} \cdot ((u - \|Y_i - Y\|^2)/u)^{M^Z}}{\sum_{i=1}^{M} ((u - \|Y_i - Y\|^2)/u)^{M^Z}}\right) \tag{1}$$

where M denotes the number of patterns in the PBHC, $X_i, Y_i, i = 1, \cdots, M$ represent the stored patterns, X or Y is the initial vector presented to the network, x_k and x_{ik} denote the kth digits of X and X_i, respectively, y_k and y_{ik} represent the kth digits of Y and Y_i, respectively, Z is a positive integer, u denotes a function defined as the following equation

$$u = \sum_{i=1}^{M} \sum_{j=1}^{M} \|X_i - X_j\|^2 + \|Y_i - Y_j\|^2 \tag{2}$$

and $H(\cdot)$ is a staircase function shown as the following equation

$$H(x) = \begin{cases} 0, & x < 1/(2\lambda) \\ \lfloor x + 1/(2\lambda) \rfloor, & \text{elsewhere.} \end{cases} \tag{3}$$

The graphic representation of the staircase function $H(\cdot)$ is shown in Fig. 1. Note that if $\lambda \to \infty$, then $H(x) \approx x$ for $x \in [0,1]$. Besides, u is bounded according to (3).

B. Energy Function and Stability

The fact that every stored pattern pair should produce a local minimum on the energy surface to be recalled correctly accounts for why the energy function is intuitively defined as

$$E(X, Y) = \sum_{i=1}^{M} \|X - X_i\|^2 \cdot \|X - Y_i\|^2. \tag{4}$$

Fuzzy data model using PBHC can be viewed as one kind of BAM. Therefore, its stability can be elucidated by closely examining its two phases of evolution, i.e., $X \to Y$ and $Y \to X$. We have adopted the SNR approach to compute the theoretical capacity of PBHC in the average case without considering fault tolerance, which is $M = (1 + \lambda)^n/2$ [1].

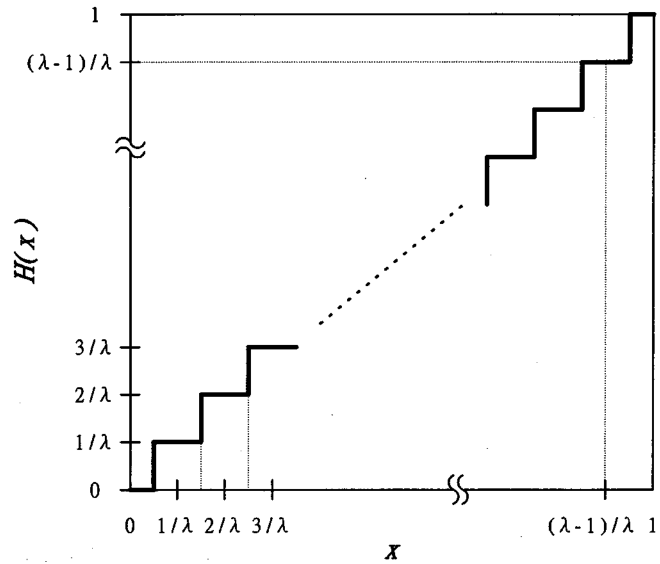

Fig. 1. The staircase function.

C. Analysis of the Capacity of PBHC with Fault Tolerance

Considering the required fault tolerance capability, we need to enlarge the area where the stored patterns reside. We introduce a basin concept to the storage of patterns. The radius of the basin where the target pattern locates is termed the attraction radius r. In other words, when the input pattern is located in this basin, the PBHC should be able to recall the target pattern. For instance, suppose we initialize the PBHC with an input pattern X. If the distance between X and X_h (the target pattern) is less than or equal to r, this input pattern X is expected to recall the target pattern X_h and its corresponding pattern Y_h. We, thus, have the following conclusion.

Theorem 1: If $\|X_h - X\| \le r$ and the PBHC can recall X_h given X, then that the maximal capacity for a fuzzy PBHC to store pattern pairs in the average case is

$$M < M_{\max} = \left\{\frac{(1/2)\ln(6\lambda/((M-1)\cdot(2\lambda+1)))}{\ln((u - (n/9)\cdot((\lambda+2)/(\lambda+1))^2)/(u - r^2))}\right\}^{Z^{-1}}. \tag{5}$$

Proof: According to (1), we will only discuss the Y part of the evolution equations without any loss of robustness here. We can rewrite the left-hand side of (1) as

$$\begin{aligned} y_k \cdot \sum_{i=1}^{M} \left(\frac{u - \|X_i - X\|^2}{u}\right)^{M^Z} &= \sum_{i=1}^{M} y_{ik} \left(\frac{u - \|X_i - X\|^2}{u}\right)^{M^Z} \\ &= y_{1k} \cdot \left(\frac{u - \|X_1 - X\|^2}{u}\right)^{M^Z} + \cdots \\ &\quad + y_{hk} \left(\frac{u - \|X_h - X\|^2}{u}\right)^{M^Z} + \cdots \\ &\quad + y_{Mk} \left(\frac{u - \|X_M - X\|^2}{u}\right)^{M^Z}. \end{aligned} \tag{6}$$

The largest noise that can appear is in the case which any X_i, $i \ne h$, is just one component different from X_h (assume that X is the input pattern and Y_h is recalled expectantly). Meanwhile, the

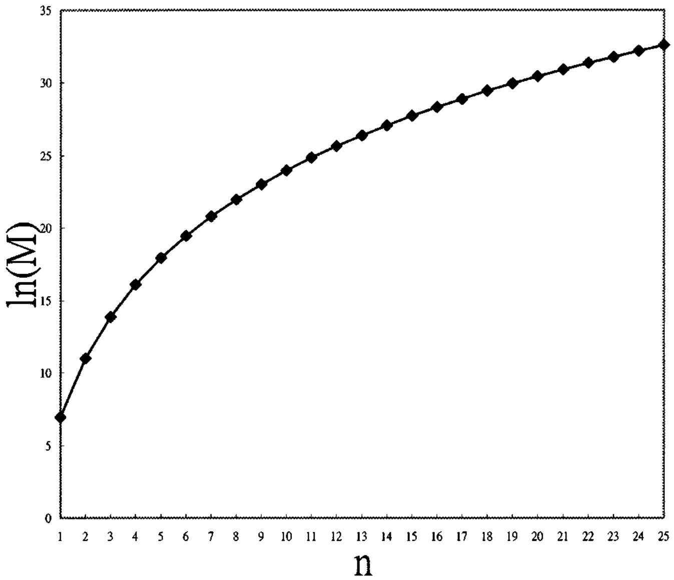

Fig. 2. The capacity of the PBHC in the average case without fault tolerance radius.

other components of X_i and X_h remain the same. For instance, $X_h = (x_{h1}, x_{h2}, \cdots, x_{hn})$, and $X_i = x_{i1}, x_{i2}, \cdots, x_{in} \pm 1/(2\lambda))$, where $x_{ik} \in \{0/\lambda, 1/\lambda, \cdots, \lambda/\lambda\}$, $k = 1, 2, \cdots, n$, and $y_{ik} \in (0/\lambda, 1/\lambda, \cdots, \lambda/\lambda\}$, $k = 1, 2, \cdots, p$. We substitute the $\|X - X_i\|$ with the attraction radius r in (6). Equation (6), thus, can be rewritten as

$$\begin{aligned}\sum_{i=1}^{M} y_{ik} \left(\frac{u - \|X_i - X\|^2}{u}\right)^{M^Z} &= \sum_{i=h} y_{ik} \cdot \left(\frac{u - \|X_i - X\|^2}{u}\right)^{M^Z} \\ &\quad + \sum_{i \neq h}^{M} y_{ik} \cdot \left(\frac{u - \|X_i - X\|^2}{u}\right)^{M^Z} \\ &= y_{hk} \cdot \left(\frac{u - r^2}{u}\right)^{M^Z} + \sum_{i \neq h}^{M} y_{ik} \left(\frac{u - \|X_i - X\|^2}{u}\right)^{M^Z} \qquad (6a)\end{aligned}$$

where y_k, y_{ik}, and y_{hk} represent the kth digits of Y, Y_i, and Y_h, respectively. The first term in (6a) corresponds to the signal, and the other terms are the noise. The power of the signal is $S = [((u - r^2)/u)^{M^Z}]^2$. Besides the first term, the remaining terms are actually the sum of $M - 1$ independent identically distributed random variables. Therefore, the noise of these terms is $M - 1$ times of the noise of a single random variable. Assume $h = 1$ for the sake of clearness. That is, $X_1 = X$ is the input pattern pair and Y_1 is recalled expectantly. Substituting X_1 for X allows us to rewrite (6), and we let

$$\begin{aligned} v_1 &= y_{1k} \cdot \left(\frac{u - \|X_1 - X_1\|^2}{u}\right)^{M^Z} \cdots \\ v_M &= y_{Mk} \cdot \left(\frac{u = \|X_M - X_1\|^2}{u}\right)^{M^Z}. \end{aligned} \qquad (6b)$$

Since all of the v_i's, $i = 2$ to M, have the same property, we select v_2 as the sample. By assuming that $X_1 = (x_{11}, x_{12}, \cdots, x_{1n})$, $X_2 = (x_{21}, x_{22}, \cdots, x_{2n})$, then we can get

$$\Delta x_{21} = \|x_{21} - x_{11}\| \in \{0/\lambda, 1/\lambda, \cdots, 1/2, \cdots, \lambda/\lambda\}. \qquad (7)$$

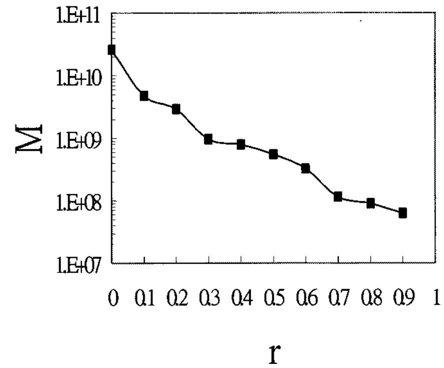

Fig. 3. The practical capacity of PBHC in the average case with fault tolerance radius ($n = p = 10, \lambda = 10, Z = 2$).

TABLE I
THE PRACTICAL CAPACITY OF PBHC
($n = p = 10$, $\lambda = 10$, $Z = 2$)

r	M	*ln*M	r	M	*ln*M
0.0	2.594×10^{10}	23.98	0.5	5.584×10^{8}	20.14
0.1	4.719×10^{9}	22.28	0.6	3.276×10^{8}	19.60
0.2	2.935×10^{9}	21.80	0.7	1.137×10^{8}	18.55
0.3	9.681×10^{8}	20.69	0.8	8.945×10^{7}	18.31
0.4	7.892×10^{8}	20.49	0.9	6.289×10^{7}	17.96

Also assume that Δ is the difference of a fuzzy bit (fit). It is trivial to derive the following probability function for the difference of a fuzzy bit (fit)

$$\begin{aligned} P_{\text{fit}}\left(\Delta x_{21} = \frac{0}{\lambda}\right) &= \frac{\lambda + 1}{(\lambda + 1)^2} \\ P_{\text{fit}}\left(\Delta x_{21} = \frac{1}{\lambda}\right) &= \frac{2 \cdot (\lambda - 0)}{(\lambda + 1)^2} \cdots \\ P_{\text{fit}}\left(\Delta x_{21} = \frac{\lambda}{\lambda}\right) &= \frac{2 \cdot [\lambda - (\lambda - 1)]}{(\lambda + 1)^2} = \frac{2 \cdot 1}{(\lambda + 1)^2}. \end{aligned} \qquad (8)$$

Hence, the general form of probability function for the difference of a fuzzy bit (fit) can be derived as follows,

$$P_{\text{fit}}\left(\Delta x_{21} = \|x_{21} - x_{11}\| = \frac{g}{\lambda}\right) = \frac{2 \cdot (\lambda - g + 1)}{(\lambda + 1)^2} \qquad (9)$$

where $1 \leq g \leq \lambda$. In addition, we can derive the expectation value for the difference of a fit as follows:

$$\begin{aligned} &E(\Delta x_{i1} = \|x_{i1} - x_{11}\|) \\ &\quad = \sum_{q=1}^{\lambda} \frac{q}{\lambda} \cdot \frac{2 \cdot (q + 1)}{(\lambda + 1)^2} = \frac{(\lambda + 2)}{3(\lambda + 1)}, \qquad i = 2 \text{ to } M. \end{aligned} \qquad (10)$$

The expectation value of the square of the difference of a fit can also be derived as follows:

$$\begin{aligned} &E(\Delta x_{i1}^2 = \|x_{i1} - x_{11}\|^2) \\ &\quad = \sum_{q=1}^{\lambda} \left(\frac{q}{\lambda}\right)^2 \cdot \frac{2(\lambda - q + 1)}{(\lambda + 1)^2} = \frac{(\lambda + 2)}{6\lambda}, \\ &\qquad i = 2 \text{ to } M. \end{aligned} \qquad (11)$$

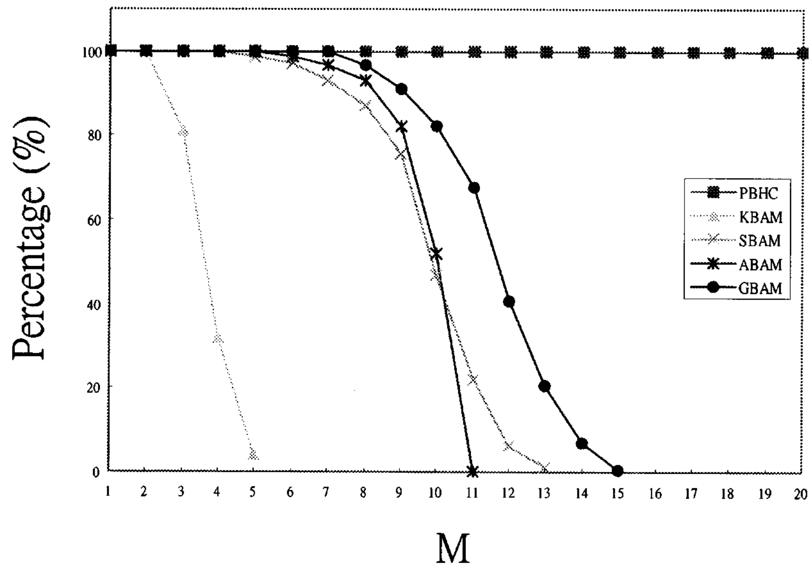

Fig. 4. Comparison of storage capacity of PBHC, KBAM, SBAM, ABAM, and GBAM. (The x-axis represents number of stored pattern pairs (i.e., value of M), while the y-axis represents the percentage of correct convergence when the patterns in the X-space are presented to the memory.)

The mean of one noise term can be derived as

$$\begin{aligned} E(v_i) &= E\left(\left(\frac{u-\|X_i-X\|^2}{u}\right)^{M^Z}\right)\cdot E(y_{ik}) \\ &= E\left(\left(\frac{u-\|X_i-X\|^2}{u}\right)^{M^Z}\right)\cdot \sum_{q=0}^{\lambda}\frac{q}{\lambda}\cdot\frac{1}{\lambda+1} \\ &= \frac{1}{2}\,E\left(\left(\frac{u-\|X_i-X\|^2}{u}\right)^{M^Z}\right), \quad i=2 \text{ to } M. \end{aligned} \tag{12}$$

The expectation value of the power of one noise term can be derived as

$$\begin{aligned} E(v_i^2) &= E\left(\left[\left(\frac{u-\|X_i-X\|^2}{u}\right)^{M^Z}\right]^2\right)\cdot E(y_{ik}^2) \\ &= E\left(\left[\left(\frac{u-\|X_i-X\|^2}{u}\right)^{M^Z}\right]^2\right)\cdot \sum_{q=0}^{\lambda}\frac{1}{\lambda+1}\left(\frac{q}{\lambda}\right)^2 \\ &= E\left(\left[\left(\frac{u-\|X_i-X\|^2}{u}\right)^{M^Z}\right]^2\right)\cdot\frac{2\lambda+1}{6\lambda}, \\ &\quad i=2 \text{ to } M. \end{aligned} \tag{13}$$

The SNR must be greater than one to recall the correct pattern pair, i.e.,

$$\begin{aligned} \text{SNR} &= \frac{\text{Signal Power}}{\text{total Noise Power}} \\ &= \frac{S}{(M-1)\cdot\text{Noise}} \\ &= \frac{\text{Signal}}{(M-1)\cdot(\text{Noise term's Variance})} > 1. \end{aligned} \tag{14}$$

The variance of noise can be derived as $\text{Var}(v_i) = E(v_i^2) - E^2(v_i)$, since $E(v_i^2) > E(v_i^2) - E^2(v_i)$, thus, the following inequality can be obtained:

$$E(v_i^2) > \text{Var}(v_i). \tag{15}$$

The above upper bound in (15) is the maximal noise power, called $N_{\max}$, which is equal to $E(v_i^2)$. Then, the ($\text{SNR}_{\min}$) of the PBHC is shown in (16) at the bottom of the page. Next, the maximal Z in the average case for PBHC is derived to accurately recall every stored pattern pair according to (16) as follows:

$$\begin{aligned} Z &< \frac{1}{\ln M} \\ &\quad\cdot \ln\left\{\frac{(1/2)\,\ln[6\lambda/((M-1)\cdot(2\lambda+1))]}{\ln[(u-n((1/3)\cdot(\lambda+2)/(\lambda+1))^2)/(u-r^2)]}\right\}. \end{aligned} \tag{17}$$

According to (16), the capacity can also be derived as follows:

$$M < \left\{\frac{(1/2)\,\ln[6\lambda/((M-1)\cdot(2\lambda+1))]}{\ln[u-n((1/3)\cdot(\lambda+2)/(\lambda+1))^2)/(u-r^2)]}\right\}^{Z^{-1}}. \tag{18}$$

III. Simulation Analysis

Fig. 2 shows that the theoretical capacity of PBHC in the average case given $n = p$, $\lambda = 10$, $Z = 2$. Fig. 3 and Table I reveal that the practical capacity M of a PBHC with fault tolerance ability r will drastically decrease with the increase of the attraction radius.

Example 1: To evaluate a BAM-like associative memory, the most important thing, perhaps, is its storage capacity. The storage capacity of the GBAM [5] is a little greater than n, that of the SBAM or ABAM is

$$\text{SNR}_{\min} = \frac{S}{(M-1)N_{\max}} = \frac{\left[((u-r^2)/u)^{M^Z}\right]^2}{(M-1)\cdot\{[(u-n((1/3)\cdot(\lambda/2)/(\lambda+1))^2)/u]^{M^Z}\}^2\cdot\dfrac{2\lambda+1}{6\lambda}} > 1 \tag{16}$$

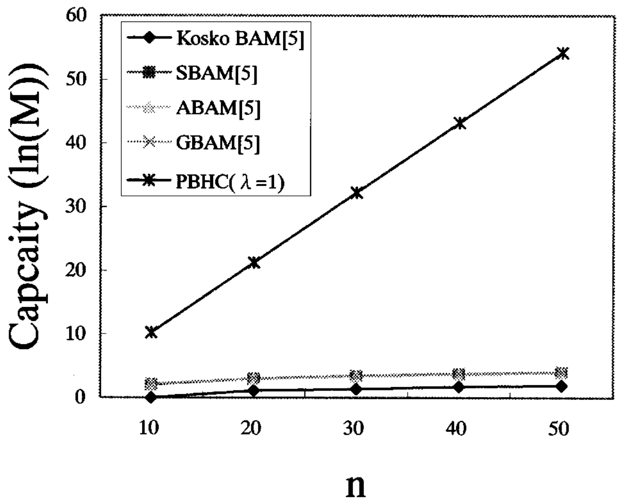

Fig. 5. Capacity comparison of the PBHC versus BAM-like heteroassociator.

closer or equal to n, and the capacity of the Kosko's rule is $\leq 0.15n$. By contrast, the PBHC provides a significantly high capacity of storage for patterns as shown in (18). The capacity of PBHC, thus, is much greater than n. In order to compare the storage capacity of PBHC with that of Kosko BAM (KBAM), SBAM, ABAM, and GBAM, we randomly generate desiredly stored pattern pairs. For the memory size $(n, p), n = p = 10$, we compute the percentage of successful tests which make all the M desired pattern pairs stable, $M = 1, 2, 3, \cdots, 20$. 1000 test sets consisting of M desired pattern pairs are randomly generated. A test is considered successful if all the M pattern pairs in the test set are stable. That is, they can be recalled correctly and correspondingly. The percentage of successful tests for the combination $(n = p = 10, M)$ is plotted in Fig. 4. If the percentage of successful tests for M pattern pairs is over 90%, we consider that M pattern pairs can be stored in the memory [5]. In Fig. 5, the previous works are plotted together to show the comparison. Because the numerical values of the PBHC is relatively much larger than those of the conventional BAMs, a log scale is used so that the contrast is more substantial. Notably, we use PBHC with $\lambda = 1$ in order to derive a fair comparison with other BAM-like designs which usually process either binary vectors or bipolar vectors. According to our simulation results, the PBHC outperforms those of previous investigations in capacity comparison.

IV. Conclusion

According to our results, the PBHC with fault tolerance ability r still provides an extremely high storage capacity for patterns. The proposed energy function ensures that every stored pattern pair is located in a local minimum of the energy surface. The practical capacity of the PBHC with fault tolerance in the average case is estimated, thereby allowing us to predetermine the size of the PBHC by the demand of capacity possible.

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