ARTIFICIAL IMMUNE SYSTEMS APPLIED TO TELLER MACHINE DIAGNOSIS

RICARDO DE CARVALHO DESTRO*, REINALDO AUGUSTO DA COSTA BIANCHI†

*Centro Universitário da FEI e Volans Informática
Av. Dr. Cardoso de Melo, 1470 - Cj. 907
São Paulo, SP, Brasil

†Centro Universitário da FEI
Av. Humberto de Alencar Castelo Branco, 3972
São Bernardo do Campo, SP, Brasil

Emails: `destro@fei.edu.br, reinaldo.bianchi@gmail.com`

Abstract— This paper explores the application of Artificial Immune Systems (AIS) as a pattern recognizer to diagnose Card Readers in Automatic Teller Machines (ATM). In fact, it extends a previous work which applied Artificial Neural Networks for the same task, using AIS as recognizer and keeping representation model intact. Attempts to use the original representation models have not reached good results, but remains open that a combination of techniques to pattern recognition can help improve the performance of diagnostic tools for ATM.

Keywords— Artificial Immune Systems, Automatic Teller Machines, Card Reader, Pattern Recognition, Machine Learning, Evolutionary Systems

1 Introduction

One of the most significant technologies for banks has been the introduction of Automated Teller Machines (ATM). The first ATM was installed in the end of 60's by Barclays Bank in the USA, and now almost all banks around the world operates an ATM network owned by themselves or by partners.

Initially, ATMs were used only for dispensing cash, but now offer a full set of services, like transfer of funds, paying bills, balances. Basically, for using ATM services, the bank issues its customer an ATM card and a PIN code. The customer inserts the card into the ATM terminal, and enters the PIN code. If the bank authenticates the PIN code, then the customer can use the ATM services.

Automated Teller Machines (ATM) are basically embedded systems made up self contained modules, like cash dispenser, card reader (for magnetic stripe cards or smart cards), bar code scanner, receipt printer, display, security devices, etc, controlled by a supervisory module, usually a personal computer. Figure 1 shows an ATM and its modules.

Today largely used by financial institutions as a service channel to their customers, due the access to an ATM network is the only way to a customer get cash when the branches are close. Added to its convenience, the complete set of transactions, the low cost of transactions (when comported with branches and call center)and the permanent concern of the banks to keep their ATM available makes tho channel one of the most popular for banks in Brazil (FEBRABAN, 2011).

From a software perspective, we can divide the components of an ATM as Figure 2. There are five main components:

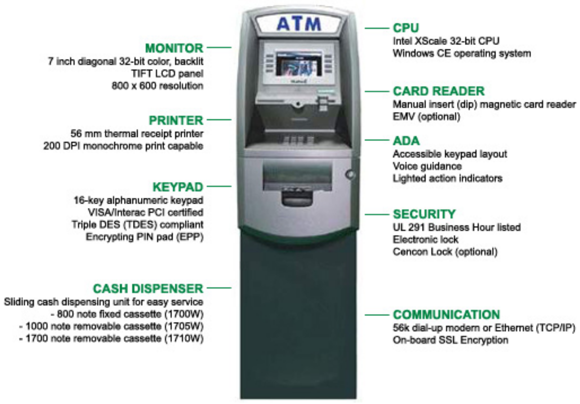


Figure 1: An example of ATM and its modules (Model: Hantel 1700)

Supervisor Application: responsible for monitoring the ATM operation.

Transactional Application: responsible for interact with clients and drive messages to perform requested transactions.

Communication Layer: responsible for send standardized messages from the both applications to the Peripherals, usually trough a proprietary protocol for each peripheral and vendor. Some well know standards for peripheral communication are XFS (eXtension for Financial Services) and J/XFS (Java eXtension for Financial Services), keep by the European Committee of Standardization (CEN - Comité Européen Normalisation).

HOST Communication: responsible for send messages form the ATM to the bank.

LOG: responsible for store operational information of all software components.

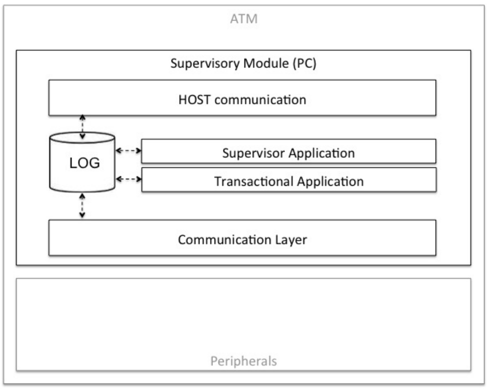


Figure 2: ATM software modules

Figure 3 shows a simple ATM network, where the equipments are connected to a host, responsible to authorize transactions at ATM. The brazilian market has today almost 200 thousand ATM, divided in few, but huge, networks without interoperability between them. Actually, there is only one shared network which can be used by customers from multiple banks (FEBRABAN, 2011).

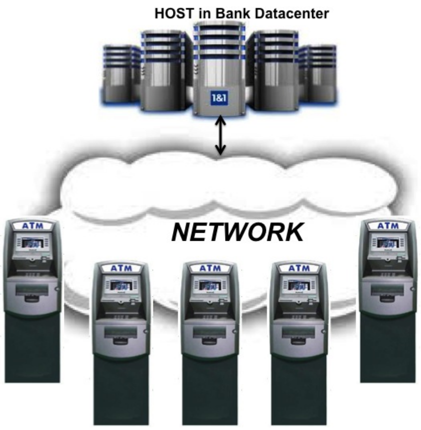


Figure 3: ATM network

The diagnosis process on ATM equipment tries to figure out the presence of a defect based on observations. Besides this definition is not precise and formal, its reveal two main aspects to solve the diagnosis process: the set of relevant data available and the analysis of this data to estimate the equipment defect.

Even without improving the Mean Time Between Failures of the ATM, use a software tool to diagnose the equipment unavailability is a way to decrease the period of time to figure out the problem and, consequently, the Mean Time to Repair (MTTR). Considering the Availability can be defined as equation 1, a good diagnostic solution for ATM can increase ATM availability (Aguiar et al., 2000).

$$Availability = \frac{MTBF}{MTBF + MTTR} \qquad (1)$$

2 Artificial Immune Systems

The vertebrate immune system is composed of a range of cells and molecules that work together with other systems in order to maintain a steady state within the host and protect bodies from infectious agents such as viruses, bacteria, fungi and other parasites (Janeway, 2001).

From nature, we can simply consider there to be two types of immunity: innate and adaptive. Innate immunity is not directed towards specific invaders, but against general properties of pathogens that enter the body, and it plays a vital role in the initiation and regulation of immune responses, including adaptive immune responses.The adaptive immune system is directed against specific invaders, and its agents within the system are modified by exposure to such invaders (Janeway, 2001).

The effectiveness of natural immune systems are basically based on the different timescale of innate immune system and the adaptative immune system. The first one has a quick response, whilst the adaptive one operates over a longer time period (Timmis et al., 2010).

Artificial Immune Systems (AIS) are problem solving systems inspired on nature and can be defined as *an adaptive system, inspired by theoretical immunology and observed immune functions, principles, and models that are applied to problem solving* (de Castro and Timmis, 2002).

We can find a myriad of algorithms inspired on immune systems applied to solving problems (Hart and Timmis, 2008)(Ulutas and Kulturel-Konak, 2011), with different degrees of success.

The most common algorithms are inspired by the immunological processes of negative selection (which has been extensively used in anomaly detection) and clonal selection (applied to a wide range of optimization and clustering problems) (Garrett, 2005).

Despite the alignment with Evolutionary algorithm is not so clear on Pattern Recognition (McEwan and Hart, 2011), AIS applied as a pattern recognizer has some shared characteristics with another very common technique: Artificial Neural Networks (ANN). Basically both of them may be divided in three stages: 1) Defining the representation for the patterns; 2) adapting (learning or evolving) the system using a training set of data; and 3) run the system to identify new sample or a set of new samples (de Castro and Timmis, 2002).

2.1 Clonal Selection

Clonal Selection is based on adaptation process of B-cells, which involves high rates of proliferation (cloning) and mutation to generate a population of B-cells capable to avoid the proliferation of foreign cells (antigens) (McEwan and Hart, 2011).

As an AIS algorithm, Clonal selections requires a set of data (antigens) to be matched with a repertoire of antibodies. High rates of cloning and low rate of mutation will be applied on antibodies with high degree of antigen matching (Figure 4) (de Castro and Timmis, 2002).

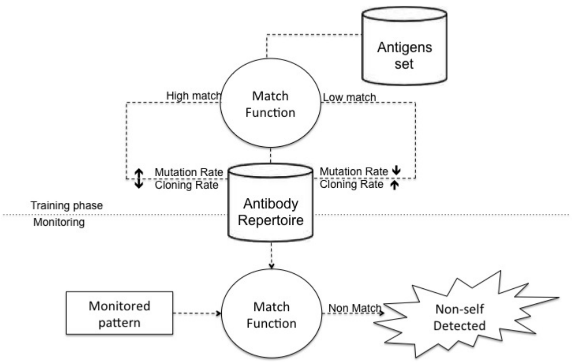


Figure 4: Clonal Selection algorithm for pattern recognition. Training and monitoring.

2.2 *Negative Selection*

Negative Selection is based on the natural process of maturation of T-cells, which takes place on thymus, to send tolerant T-cells to circulate to body. Tolerant cells means cells that do not respond do self (de Castro and Timmis, 2002).

As an AIS algorithm, Negative Selection needs a set of patterns for training, called self-set, to generate a set of detectors. On training phase, the algorithm creates a set of candidates to detector and these candidates and eliminated if they match with any sample of training set, otherwise, they are stored on the detectors set. On monitoring stage, a pattern which matches with any detector pattern is detected as a non-self pattern (Figure 5) (Elberfeld and Textor, 2011).

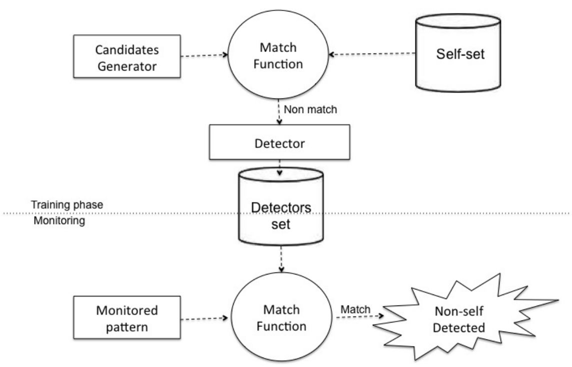


Figure 5: Negative Selection algorithm for pattern recognition. Training and monitoring.

3 AIS to diagnose ATM

On this work, an AIS was embedded on ATM and use the LOG module to capture information. Figure 6 changes the architecture presented on figure 2 to include the diagnostic module.

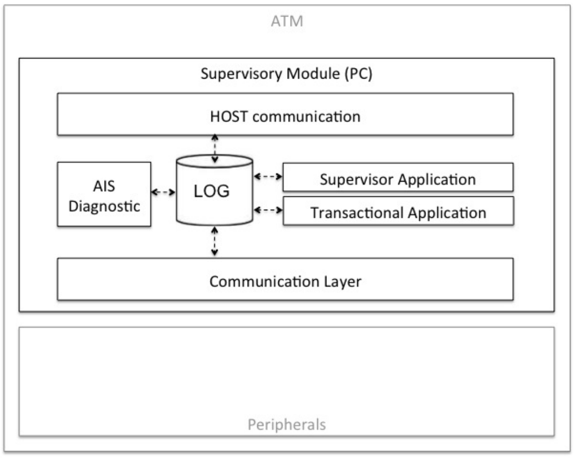


Figure 6: ATM software modules with AIS Diagnostic

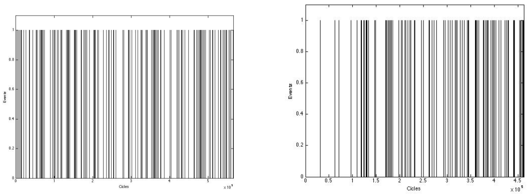
As the proposed architecture do not include an external agent connected to a centralized host for diagnostic (like in (De Lemos et al., 2007)), the data sets for training was collected using a direct access to log files on ATM and these files were stored on the research's database (Destro et al., 2012). To this work, we selected only the log events related with Card Reader and each registry stored in the database has: ATM identification, the hundred last fault events (as will be explained on Figure 7 and the real status of the Card Reader: with or without defect.

This work makes use of the same database presented in (Destro et al., 2012), with 1,000 samples of deteriorated card readers and 1,000 samples with non-deteriorated samples.

Usually, any malfunction on Card Reader turns ATM unavailable to the customers(Destro et al., 2012), because almost all services offered on ATM requires the customer's card and a password to identify the customer and complete the transaction.

Besides Card Reader is a cheap module in ATM, a problem on this module avoids customers to use the whole equipment.Only a few services can be done using only the password and account number and, most recently, using the password and biometry information.

Faults caused by external agents do not involve problems with the module, but rather with the environment where it is being used. However, on Card Reader module, they make it appear as if there has been a functional problem (as a card not read at ATM log file), and the fault diagnosis system must be capable of identifying when a sequence of faults arises from a defect or problem in the module, or from the environment. Figure 7a shows error events usually present on a Card Reader without defect and figure 7b, the events form a Reader with problems.



(a) Events on Non degraded Reader (b) Events on Degraded Reader

Figure 7: Fault events on card reader

As an example of this interference, card readers are highly sensitive to the manufacturing quality of the magnetic strips, since when extremely worn out these require a reader head in almost ideal working condition, so that no fault is observed while reading. Another example is motor-based positioning systems whose working path is subject to blockage by objects being inserted along their path, or due to lack of lubrication on the running tracks, leading to a positioning fault even though there is no actual problem with the functioning of the module.

Each individual behavior presented on figure 7 comprises a vector of [100x1] dimension, with the 100 last fault events registered on log file, whose values are indicative of the order of the operation in which the fault occurred, being therefore strictly ascending. For example, a given individual has a behavior described by the vector [26;63;...;272;351], indicating the last fault which occurred in the operation 351, while the first stored fault occurred at 26^{th} operation (Destro et al., 2012).

As described on section 2.2, the first step of Negative Selection training phase is generate the candidates do detectors. Using the representation described above, to randomly generate a candidate which matches a sample has a probability lower than 10^{-100} , due the dimension of each vector (Luo et al., 2008), which is obviously computationally unfeasible for our purposes.

One alternative to turn the approach with Negative Selection feasible is to reduce the dimension of each sample, which means, reduce the historical of operation for each sample. Actualy, in (De Lemos et al., 2007) this windows size is of the 6 or 14 last error(log) events.

Due the nature of defects in card reader, table 1 shows the impact of the reduction in windows size from *the last 100 error events* to *errors in last 100 operations.* With a population varying from 15 to 60 detectors and the Hamming distance as match function, the Negative Selection algorithm was not able to correct identify the patterns for degraded readers.

Data set		Set Size	Misclassification		
			15	45	60
Degraded	Training	750	0.3%	0.0%	0.0%
	Test	250	1.2%	2.4%	2.6%
Non Degraded	Test	1,000	97.1%	95.9%	95.3%

Table 1: Negative Selection Algorithm: percentage of misclassification with 15, 45 and 60 detectors

Table 1 clearly shows that even using a small amount of detectors is easy to over fit the training set and to cover almost all monitored shape space.

On the other hand, using Clonal Selection algorithms we did not have to handle with random generations of candidates at offline (training) phase. Once created the initial antibody repertoire 4, all other candidates are created with an heuristic based on their affinity with antigens. Figure 8 show an generic algorithm for clonal selection.

```
Initialize antibody repertoire
Do
Evaluate antibodies repertoire
Clone antibodies
Mutate cloned antibodies
Eliminate antibodies with low affinity
Insert few aleatory antibodies
While do not reach stop criteria
```

Figure 8: Pseudocode for Clonal Selection Algorithm

Applying the same representation as above to Negative Selection, but now using the Degraded Card Readers database, again we found very poor results. Table 2 shows the result with a repertoire of 50 antibodies, Hamming distance as match function and linear functions to change rates of mutation and cloning, depending on affinity measured.

Data set		Set Size	Misclassification
Non Degraded	Training	750	0.1%
	Test	250	2.1%
Degraded	Test	1.000	96.1%

Table 2: Clonal Selection Algortihm: percentage of misclassification

Both Table 1 and Table 2 are consistent to result that the simplification to drastically reduce dimension of log sample, to keep reasonable to generate repertoires, directly impairs the AIS performance.

Instead reduce the log sample, uses the original data presented in (Destro et al., 2012) the results are a somewhat better than de previous ones, as show in table 3, but still far from a definitively result to be applied on deployed versions of the diagnostic tool. This simulation used Hunter Distance, besides Hamming Distance and the repertoire of antibodies varying from 40 to 100 samples.

Data set		Set Size	Misclassification			
			40	60	80	100
Non Degraded	Training	750	1.0%	0.4%	0.0%	0.0%
	Test	250	1.2%	1.1%	0.3%	0.0%
Degraded	Test	1,000	59.4%	67.3%	36.1%	33,4%

Table 3: Clonal Selection Algorithm: percentage of misclassification with antibodies repertoire varying from 40 to 100 samples

4 Conclusion

Whilst share important concepts with well known pattern recognizers, like Artificial Neural Networks, the attempting to use a data representative model already available and validated in ATM with diagnostic based on ANN, due the poor results presented on this work, AIS needs a complete new design of data representation, mainly for negative selection algorithms. This observation brings a new challenge to create fully hybrid systems of diagnostic, capable to deal with different failure behavior of components on the same equipment.

Due the nature of immune systems and ATM equipments, an approach to detect errors on ATM using AIS as presented in (De Lemos et al., 2007), with a centralized management tool capable of consolidate information from the entire network and broadcast new parameters should also improve the performance of algorithms after representation redesign.

5 Acknowledgment

Ricardo Destro wants to acknowledge the Centro Universitário da FEI and Volans Informática for the financial support on his research.

Reinaldo Bianchi acknowledges the support of the FAPESP (grants 2011/19280-8, 2012/04089-3 and 2013/17286-4).

References

Aguiar, M. A., Destro, R. C. and Kovács, Z. L. (2000). Reliability and fault diagnosis in an atm cash dispenser, *Proceedings of INDUSCON'00*.

de Castro, L. and Timmis, J. (2002). Artificial immune systems: A novel paradigm to pattern recognition, *Artificial Neural Networks in Patter Recognition* pp. 67 – 84.

De Lemos, R., Timmis, J., Ayara, M. and Forrest, S. (2007). Immune-inspired adaptable error detection for automated teller machines, *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on* **37**(5): 873–886.

Destro, R. C., Aguiar, M. A. and Furucho, R. A. (2012). Diagnóstico de falhas em sistemas degradados utilizando técnicas de redes neurais artificiais, *Proceedings of 7 Ibero American Congress on Sensors*.

Elberfeld, M. and Textor, J. (2011). Negative selection algorithms on strings with efficient training and linear-time classification, *Theor. Comput. Sci.* **412**(6): 534–542.

FEBRABAN, F. B. d. B. (2011). Pesquisa febraban de tecnologia bancária 2013 - o setor bancário em números, *Technical report*, FEBRABAN.

Garrett, S. (2005). How do we evaluate artificial immune systems?, *Evolutionary Computation* **13**(2): 145–177.

Hart, E. and Timmis, J. (2008). Application areas of ais: The past, the present and the future, *Applied Soft Computing* **8**(1): 191–201.

Janeway, C. (2001). *Immunobiology*, Garland Science.

Luo, W., Guo, P. and Wang, X. (2008). On convergence of evolutionary negative selection algorithms for anomaly detection, *Evolutionary Computation, 2008. CEC 2008. (IEEE World Congress on Computational Intelligence). IEEE Congress on*, pp. 2933–2939.

McEwan, C. and Hart, E. (2011). On clonal selection, *Theoretical Computer Science* (412): 510–516.

Timmis, J., Andrews, P. and Hart, E. (2010). On artificial immune systems and swarm intelligence, *Swarm Intelligence* **4**(4): 247–273.

Ulutas, B. H. and Kulturel-Konak, S. (2011). A review of clonal selection algorithm and its applications, *Artificial Intelligence Review* pp. 1–22.