Elaboration of an artificial model for filtering of spam based on Human Renal Function

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Abstract. In today's world of globalization and borderless technology, the explosion in communication has revolutionized the field of electronic communication. The e-mail is therefore one of the most used methods for its efficiency and profitability. In the last few years, the undesirables emails (SPAM) are widely spread as they play an important part in the inbox. so that such emails must be filtered and separated from those non-SPAMS (HAMS). Consequently, several recent studies have provided evidence of the importance of detection and filtering of SPAM as a major interest for the Internet community.
In the present paper, we propose a meta-heuristic based on the renal system for detection and filtering spam. The natural model of the renal system is taken as an inspiration for its purification of blood, the filtering of toxins as well as the regularization of the blood pressure.The message are represented by both a bag words and N-Gram method method which is independent of languages because an email can be received in any language

Keywords: SPAM Detection, SPAM filtering, F-Measure, Recall, Precision, Renal System, Nephron, Bowman's capsule, Glomerulus, afferent artery, efferent artery, blood flow , primitive urine , kidney, reabsorption, secretion, Malpighian pyramids , Loop of Henle, proximal tubule, distal tubule, ADH stimulus, ADH inhibition.

1 Introduction and problematic

The appearance of the Internet and the incredibly rapid development of telecommunication technology have made the world a global village. The Internet has become a major channel for communication. Email is one among the tools for communication that Internet users take advantage of as it is available free of charge and supplies the transfer of files.

According to the most recent report of the Radicati Group (2013), who supplies quantitative and qualitative researches with details on the e-mail, the security, the Instant messaging (IM), the social networks, the archiving of the data, the regulatory compliance, the wireless technologies, the Web's technologies and the unified communications, there was exactlly:

- 2.9 trillion of active emails accounts in the world.
- 2.4 Billion people who use e-mails regularly and they will be 3 % more by year from 2013 till 2017 to be exceeding 2.7 billion people.
- 67 trillion is the number of e-mails that are sent to by the year 2013,that is to say, 182.9 billion every day in the world on average. This number will increase to 206.6 billion in 2017.
- 1,6 is the number of accounts detained by each person and which should increase to 1,8 in four years.

According to the same reports of the Radicati Group,unsolicited mail, or SPAM, can reach more than 89,1 %; 262 million SPAMS a day. In 2009, about 81 % of the sent emails were SPAM. Consequently, spamming became a global phenomenon. For the CNIL(the National Commission for Computing and Liberties), " the "SPAMMING" or" SPAM " is to send massive and sometimes repeated electronic mail, not requested, to people with whom the sender has had no contact and whose he has captured the email address in an irregular way. "

From the above statistics, the detection and filtering of spam is a major stake to the Internet community making the detection and filtering of spam a crucial task.

The literature gives two broad approaches for the filtering and the detection of SPAM: The approach based on the machine learning and the approach not based on the machine learning. The first approach is based on feature selection which is an important stage in the systems of classification. It aims to reduce the number of features while trying to preserve or improve the performance of the used classifier. On the other hand, the second approach (not based on the machine learning) is based on many existing techniques and algorithms: content analysis, the block lists, black lists and white lists, the authentication of mailbox and the heuristics and finally meta-heuristics.

Even though it is usually easy to decide whether it is a spam / non-spam" by human, we can't tackle SPAMS by manual sorting of email because the number of emails in circulation which we have just quoted is extremely large.

In the human body, an important process for the survival occurs automatically, which is the purification of the blood by the renal system. The human can die if the rate of toxins and unwanted substances found in the blood exceeds some threshold; the renal system purifies and filters the blood in automatic manner and a delicate and precise way. The blood pressure regulation is another role of the renal system.

We propose a method inspired from the renal system for the detection and the filtering of the SPAM with a hybridization of both approaches (based and not based on the machine learning). Further, several techniques in the same system of filtering of SPAM are used including: content analysis, the blacklists, the white lists. Another part of our approach controls the flow of the emails which represents one of the roles of the renal system (the blood pressure regulation) to minimize the risk of DDoS attacks (denial of service attack).

Our approach is a combination of different positive properties of these techniques of filtering at various levels by deploying them in a hybrid approach. This study thus seeks to answer the following research questions:

- Does the meta-heuristic based on the renal system assure more results and protection?
- Does the hybridization of the approaches and the use of several techniques improve the quality of the result of the system of filtering of SPAM?

2 Our proposed approach

Our work aims at modelling a method bio-inspired which is the renal System to problems in computer science, in this case the detection and the filtering of the SPAM. Before explaining and detailing our approach we must describe at first the natural model of the functioning of the renal system and shed light on the aspects which directed us to choose this metaheuristics for our problem which is the detection and the filtering of the SPAM. Then we draw up a table of modelling (the natural model vs the artificial model). Finally we shall explain the artificial model which is the pulp of our approach.

2.1 Natural Model

Why the renal system for filtering of SPAM?.

The role of the renal system is to cleanse, purify the blood and adjust the tension. We have chosen modeling the renal system in order to filter SPAM after the overlap which is explained in details in the following table:

	The renal system	The filtering of SPAM
INPUT	Blood	Text (Messages or email)
Result Or OUTPUT	two outputs: • Purified blood which comes back to the bloodstream • Urine which moves towards the bladder and then outside the body The regularization of the blood pressure is another aspect of the renal system.	two classes: • HAM • SPAM
Type of process	Automatic and continuous in time	Automatic and continu-ous in time
Fault tolerance	A human subject can live with only one kidney.	The filtering of SPAM must tolerate the break-downs and bugs.

Table 1. Overlapping between the renal system and the filtering of SPAM

Obviously, this overlapping gives a preliminary idea onto the feasibility of this modelling. Another argument that we have taken into consideration is that the functioning of the renal system is automatic (independent of the brain) and very precise as any error in the functioning of the renal system can be fatal or seriously pathological for the human subject.

Functioning of the Renal System.

The Nephrons are supplied by two capillary systems:

- The glomerulus where a glomerular filtration occurs to produce the primitive urine.
- The peritubular capillary network where the processes of reabsorption and of secretion it produce, once these two processes finished one will have the definitive urine.

The functioning of renal System is divided into two stages:

Step1 : the glomerular filtration.

The blood comes from the afferent arteriole and enters the glomerular room (glomerulus + Bowman capsule) to undergo the glomerular filtration.

Glomerular filtration is a nonselective, passive mechanical process: it does not consume energy; the blood pressure in the capillary the glomerular represents the dynamic element of the filtration. It is not selective because any molecule which has a size smaller than the Bowman's capsule hole will be filtered. The glomerular filtration stops when the blood pressure falls below 60 mm Hg.

Once the step was finished, the primitive urine follows the path of renal tubule where its composition will be modified during the second step; filtered blood primitively joined the efferent arteriole, the efferent arteriole will bypass the renal tubule forming the peritubular capillary network.

Step 2: renal tubular transfer.

The composition of the primitive urine produced by glomerular filtration will be modified in the renal tubule by two processes which they happen in parallel:

- Reabsorption: which consists of the transfer of certain constituents of the primitive urine to the peritubular capillary i.e. to the blood (e.g. water, mineral salts, glucose ...)
- Secretion: the toxic or exogenous substances that escaped glomerular filtration are added to the tubular urine

At the connecting tubule (CNT) where will be made the control the volume and acidity of the urine by the ADH stimulus (to make the second reabsorption of water and acidified urine) or ADH inhibition (to dilute the urine and adjustment of the balance of fluid in the blood).

At the end of the process we shall have: some definitive urine which is going to be driven by ureters towards the bladder then towards the outside of the body; and the cleansed Blood which is going to join the general blood circulation (the tip of the peritubular capillary network joined the interlobular vein). Noting that the blood pressure will be stabilized in the normal upstream.

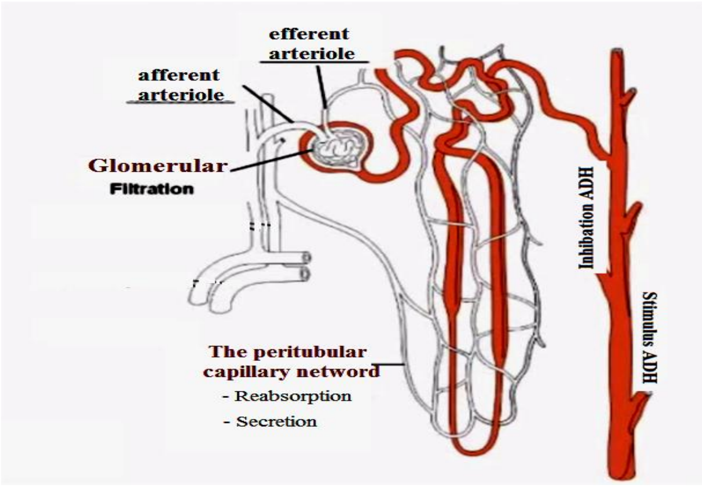

Fig. 1. Functioning of the nephron

Some specific property of the Renal System.

Before proceeding to the artificial model, we must shed light on some property of the functioning of the renal system:

- The glomerular filtration gives a quantity of the primitive urine from 150 to 180 liters per day
- The renal tubular transfer gives a quantity of the final urine from 1.5 to 2.4 liter per day
- The process of the reabsorption is more important qualitatively than that of the secretion
- Renal blood flow is equal to 20% of cardiac output i.e. 1.1 to 1.2 liters of blood per minute
- Kidney consumes 10 to 15% O^2 that it was brought by the Juxtamedullary Nephrons
- the total length of Renal tubule is equal to 115 Km
- The diameter of an afferent artery is greater than that of the efferent arteriole: this serves to:
  - Maintain blood pressure in the glomerulus (for continuity of functioning)
  - Regularization of the blood pressure

2.2 Modeling table: the transition from natural model of renal system to artificial model of renal system for filtering of spam

	natural model of renal system	artificial model of renal system for filtering of spam
New meta-heuristic based on the renal system for the filtering of	Renal consumption = **10 to 15%** of O^2	Training set = **10 to 15%** of SpamBase
	Nephron (several nephrons)	Filtering agent
	Bowman's capsule (**filter diameter**)	artificial Bowman's capsule (**the artificial filtering glomerular threshold**)
	the blood coming in Afferent arteriole is **around 20%** of the cardiac output divised by number of nephron **every minute**	Message entering to be processed is **equal to 20 %** of the total number of messages divised by the number of filtering agent, **Every iteration**
	The glomerular filtration	The artificial glomerular filtration
	Blood in efferent arteriole (before the tubular transfer)	Primitive HAM message (before the optimization)
	Primitive urine	Primitive SPAM message (before the optimization)
	The quantity of the primitive urine from 150 to 180 liters per day	Filtering before optimization must be harsh
New meta-heuristic based on the renal system for the filtering of the SPAM	The renal circulation receives around **20%** of the cardiac output **every minute**	Processing flow rate (number of message to be processed in each iteration) is equal to 20 % of total number of message **by iteration**
	Renal tubular transfer : ✓ Reabsorption ✓ Secretion	Artificial Renal tubular transfer (Optimization by K-Means) ✓ (less than False Negative) and (more of True Positive) ✓ (less than False Positive) and (more of True Negative)
	The length of the Renal tubule is equal to 115 Km	The optimization must not be limited by a number of iterations (stopping criteria must be the stagnation of the classes)
	the final result : ✓ definitive urine the outside of the body ✓ The cleansed Blood : join the blood circulation	the final result : ✓ SPAM messages definitive (after optimization) ✓ HAM messages definitive (after optimization)
	Regularization of blood pressure, and **maintain the functioning of the glomerular filtration**	**Anti DDoS attack and activate (start) and stop the process of filtering**
	types of Nephrons ✓ Cortical Nephrons ✓ Juxtamedullary Nephrons	✓ No update the training set ✓ Update the training set
	Stimulus ADH = concentrated urine	Block list and blacklist
	ADH inhibition = diluted urine	Whitelist

Table 2. Modeling table :natural model system to artificial model

In the table above we explain in general correspondence between the natural model of the renal system and the artificial model which is renal system for the filtering of the SPAM, In other words we showed the way that we interpreted and used the notions and concepts of the natural model in our artificial model which we propose. These interpretations and modeling will be explained and justified in detail in the development of artificial model in the next section.

2.3 The Artificial model of renal system for filtering of spam

In our approach dedicated to the detection and the filtering of the SPAM we suggest modelling the renal system such that the artificial model will have three states:

Initial state .

To solve the problem of filtering and detection of SPAM, we need a training set and a test set. In parallel, the training set represents the consumption of oxygen by the kidney which is between 10 to 15% of the blood supply (See table 2)

On the other hand, the test set is all the messages (SPAM and HAM) that must be treated. In equivalent with the natural model, the test set is represented by the coming blood from the afferent arteriole.

Initially, the kidneys must be active enough and well-fed to do their role appropriately. In the artificial model, we begin to fill the training set by 15 % of the number of messages.

We propose to launch two threads of the application on the server; each thread will represent a kidney. The goal of this parallelism is to accelerate the process of filtering and to give a fault tolerance so that even if a thread stops accidentally or intentionally, the other thread ensures the minimum services during the time of maintenance in addition to the re-launching of the thread which was broken down.

Moreover, each kidney contains a predefined large number of nephrons which is sufficient in our artificial model to not consume too much from the virtual memory and CPU. Nephrons are identical, i.e., the same parameters are generalized for the whole of nephrons. Obviously, the parameters of the nephrons are identical. If an email is considered SPAM by the first nephrons then it will be also considered SPAM by other nephrons and vice versa. We propose that

Each message (email) passes by only nephron randomly in each iteration

In our artificial model, 15% of the number of artificial nephrons (filtering agent) of each kidney are used to update the training set by messages after the application of the filtering process and optimization. It is the same for the juxtamedullary nephrons which feeds kidney.

State of activity .

The arrival of blood (message) by the afferent arteriole increases the blood pressure within the glomerulus and activate the process of filtration of blood (filtering of SPAM); this process is divided into two steps

Step 1: Artificial glomerular filtration:.

Before beginning this step we have to allocate to each message a score such that the HAM messages will have a high score then they not be filtered by the artificial Bowman's capsule (the sieve) and the SPAM message will have a weak score then they will filtered by artificial Bowman's capsule (the sieve).

There are several techniques and method of scoring, we have chosen to use the Bayesian classifier.

- Question 1: Why the Bayesian classifier?
- Answer 1 : “Our choice is justified by the fact that the performances of the bayesian classifier are strongly and negatively correlated with the number of class (As long as the number of class decreases, the performance of Bayesian classifier increases and vice versa). In addition to that, it allows to make a Hybridization between the approach based on Machine Learning by using the Bayesian classifier and the approach non-based on Machine Learning with our metaheuristics”

We propose to use for scoring a notion of Naive Bayes classifier, the score of each message will be equal to its probability to be HAM : In this way, each message having a big probability to be a HAM will not be filtered by the artificial Bowman's capsule and will join the efferent arteriole (classified as primitive-HAM) Whereas those who will have a weak probability to be a HAM will be filtered and will join the renal tubule (classified as primitive-SPAM)

The only change that will occur on the Bayesian classifier is in the step of class assignments. We will not assign the class according to the biggest probability, we will not even use both of two probability (SPAM and HAM).

We will define a hole diameter of the artificial Bowman's capsule (the sieve), it is **the artificial filtering glomerular threshold**; each message having a score bigger or equal to this threshold will not be filtered by the artificial Bowman's capsule and will join the efferent arteriole (classified as primitive-HAM) whilst those who will have a score smaller to the threshold will be filtered and will join the renal tubule (classified as primitive-SPAM); Let us remind that the score represents the probability that the message is a HAM by using the Bayesian classifier.

In the natural model, the glomerular filtration is very important with producing up to 180 liters of primitive urine per day, this must be taken up in the artificial model by choosing a big **artificial filtering glomerular threshold** so as to have a very harsh filtering of SPAM.

At the end of this first step we will have:

- a set of primitive SPAM that represents the primitive urine and which they will join the renal tubule.
- a set of primitive HAM that represents the filtered blood primitively and which they will join the efferent arteriole.

Noting that there are two different types of nephron, the messages which are in the juxtamedullary nephrons will be used in the next steps to update the training set.

Step 2: artificial renal tubular transfer(optimization).

The renal tubular transfer is made by two processes: Reabsorption and Secretion in the Proximal tubule, loop of Henle and distal convoluted tubule; Let us remind that these two processes will be performed in a automatic way (without intervention of brain).

At the level of the connecting tubule (CNT) two operations will be done : Stimulus ADH to get back the water from urine and Inhibition ADH to reject the water in urine. These two operations (Stimulus ADH and Inhibition ADH) are controlled by a hormone ordered by brain, therefore they are semi automatic operations.

In our work, and in parallel to the natural model; we propose to use a clustering algorithm which his initial state will be the result of the first step, since the renal tubular transfer takes in input the results of glomerular filtration.

This algorithm must represent at the same time the reabsorption process and secretion process, we propose to use the K-Means algorithm with k = 2, initially the centroids will be calculated by the classification resulting from the first step (glomerular filtration) as follows : The centroid of the HAM class will be calculated by the set of primitive-HAM (result of step 1 : glomerular filtration) likewise The centroid of the SPAM class will be calculated by the set of primitive-SPAM (result of step 1 : glomerular filtration)

- Question 2 : Why have we chosen the K-Means algorithm for modeling the renal tubular transfer?
- Answer 2 : " K-Means is the algorithm which well reflects the renal tubular transfer because :

  - The renal tubular transfer = Reabsorption + Secretion (at same times)
    - Reabsorption : transfer from the primitive urine to the primitive blood (from the SPAM-primitive class to the HAM-primitive class)
    - Secretion : transfer from the primitive blood to the primitive urine (from the HAM-primitive class to the SPAM-primitive class)

  The philosophy of the K-Means algorithm is that in every iteration: the documents changing class to join the class of which they are close to its centroid (class), in our case K = 2 (SPAM and HAM) : in each iteration, we have some messages classified as HAM who change class : from HAM class to the SPAM class (this is the secretion process) and other messages classified as SPAM who change class: from SPAM class to the HAM class (this is the reabsorption process)."

In the natural model; at the end of both processes of renal tubular transfer (reabsorption + secretion) two operations follow: the Stimulus ADH and / or the inhibition ADH.

In artificial model, we have represented the Stimulus ADH by the technique of whitelist (which will be generated by the user or the service provider) and we have represented the Inhibition ADH by the technique of blacklist (which will be also generated by the user or the service provider)

Updating of the training set.

In the artificial model 15% of nephrons are juxtamedullary nephrons, the messages which are treated by those nephrons will be used to update the training set. Let us note that messages are randomly distributed on nephrons and Let us also remind that SPAM messages (of test set) are in the renal tubule and that HAM messages (of test set) are in the peritubular capillary network which surrounds the renal tubule.

The training set must not grow up to avoid Overfitting, so we must make a crushing of the most repeated message in it to create diversity in this training set so that a maximum number of cases will be included by it (training set).

Choose a outbound HAM and a outbound SPAM from training set.

We calculate the similarity between the HAM messages in the training set and also for SPAM messages and then we calculate the centroid of each class (SPAM and HAM of training set).

We choose the most similar two HAM (SPAM respectively) (the biggest similarity for each class). We suppose that HAM1 and HAM2 (SPAM1 and SPAM2 respectively) are most similar among all HAM messages in the training set (SPAM respectively), the HAM message to crush (outbound) is the closest to the centroid of HAM class of the training set (SPAM respectively) because it is more similar to the other HAM in the training set (respectively SPAM) and we shall call it the HAM-outbound (SPAM respectively).

The HAM-outbound message from the training set will be crushed and replaced with a copy of the HAM which is in the peritubular capillary network (test set) respectively The SPAM-outbound message from the training set will be crushed and replaced with a copy of the SPAM which is in the renal tubule (test set)

The final state.

After a finite and sufficient number of iterations; All messages classified as spam, which is the final urine will be conducted outside the body (system) so that they do not return to the blood stream. All messages classified as HAM which represents the purified blood and they will join the interlobular vein.

The training set will be updated and the recommendations of the user or service provider will be taken into consideration(Blacklist and Whitelist) as a part of the training set (by the updating), let us note that the training set is quite reduced (15% of SpamBase) so this recommendations (Blacklist and Whitelist) will have a weight in decision-making by the Bayesian classifier (in probability calculation).

In the artificial model, The regularization of the blood pressure serves to limit the number of message to be treated per iteration and it can be a solution to the paralysis of the system which is caused by the spammers by a DDoS attack (denial of service) to stop the security system completely or at least make a bug in the application of filtering of SPAM. At the end of the flow of message the glomerular pressure will be equal to zero what will put the application of filtering of SPAM in paused state; If a bulk of message arrives by the afferent arteriole then the glomerular pressure increases, and will be different from zero what which will reactivate the application of filtering of SPAM.

In summary, at the end of our process that we propose, the results are:

- The SPAM class (classified as SPAM) representing the final urine.
- The HAM class (classified as HAM) representing the purified blood.
- A learning base updated to the next use (a fed kidneys).

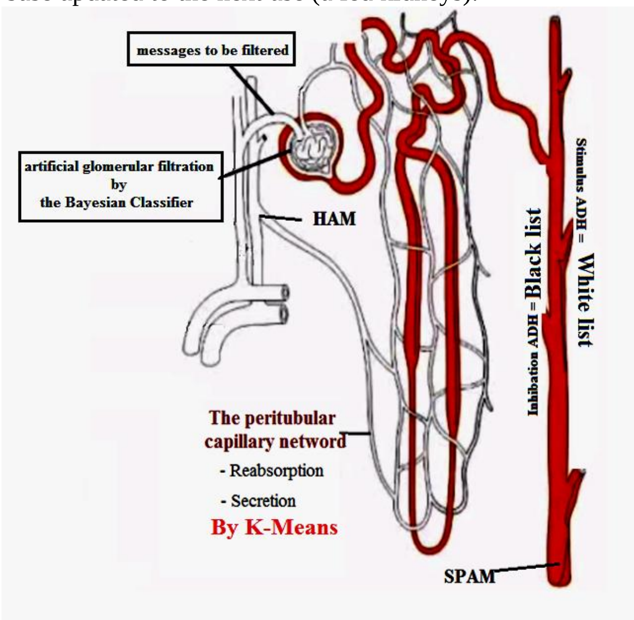

Fig. 2. artificial model vs. natural model

3 Conclusion and perspective

In this paper, we have proposed a new bio-inspired method which is the renal system. We have developed an artificial model for the detection of SPAM based on Renal Function. It is proved that this model based on the renal system is able to detect and filter the spams.

The new approach which we propose is effective and strong. Firstly,we have used the concept of Bayesian classifier which behaves well when it is applied to a classification with limited number of class (in our case the number of class is equal to two (2)); the only difference is that the class assignment is done by **an artificial filtering glomerular threshold** and not by the most majority probability. Secondly the initial state of the optimization algorithm by K-Means (the centroids) is not random, but is based on the result of the first step.

Another strong point of our approach is that the training set is not static. In fact, the training set is updated at each iteration to ensure better representativeness of possible cases and eliminate similar cases. This update is designed to take into consideration the messages we recovered / removed by technical whitelist / blacklist; So , after sufficient number of iterations that we will experiment in our future work, the training set will consider them.

Actually, our approach ensures fault tolerance by launching two threads of the application on the server, even if a thread stops accidentally or intentionally, Additionally, our approach can resist against the attack of DDoS by the regularization of pressure of treatment, even in the case of overloading of the server by an exponential number of messages our approach treats only a part of this messages at each iteration.

In the future, we plan to experiment our artificial model for the filtering of the SPAM based on human renal function and to compare its performance with other algorithms as well as other techniques of SPAM's filtering. After several experiments, we have tried to present some useful recommendations for further studies and improvement according to the results; the strengths are retained while the weaknesses are rectified and mended rather than ended. Last but not least, we plan to, hopefully, create an appropriate model of functioning parallel to our approach.

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