

METHOD, APPARATUS AND ELECTRONIC DEVICE FOR IDENTIFYING RISKS PERTAINING TO TRANSACTIONS TO BE PROCESSED

TECHNICAL FIELD

This application involves the technical field of risk control, in particular, a method, apparatus and electronic device for identifying risks pertaining to transactions to be processed.

TECHNICAL BACKGROUND

Among related technologies, more and more transactions are being processed on online platforms instead of traditional ways. Users only need to register corresponding user accounts on an online platform before he or she is able to complete transactions on the online platform using the registered user account. However, while online platforms bring convenience to transactions, they bring about security issues too. For example, if a user account is leaked, it is subject to the risk of theft and may even cause serious losses.

To address this, a risk control system has been established in the related technologies for transactions that are processed on online platforms to assess the risks of transactions, thereby detecting potential security risks as early as possible and avoiding account theft.

However, the risk control system may over-assess risks pertaining to transactions for some reasons, resulting in false positives of account theft risks even in the case where no account theft risk is existent. As a result, the transaction is required to perform user authentication, the transaction is deemed as not successfully processed, and the use account becomes restricted, thereby “disturbing” the user. The transaction is therefore an interfered transaction. Interfered transactions not only result in additional operations, lengthen the processing time, but may also reduce success rate of the transactions.

SUMMARY OF THE INVENTION

In view of this, this application provides a method, apparatus and electronic device for identifying a risk pertaining to a transaction to be processed, which can lower the improvement requirements needed for a risk control system, and improve the efficiency and accuracy of identification of transactions susceptible to interference.

To achieve the aforesaid objective, this application lists technical solutions as follows:

According to the first aspect of the application, a method for identifying a risk pertaining to a transaction to be processed, comprising:

identifying a risk pertaining to transaction to be processed via a fast identification layer in the risk control system, thereby obtaining a first identification result;

identifying a risk of interference pertaining to the transaction to be processed via a model for identifying transactions susceptible to interference, thereby obtaining a second identification result; and

determining a processing manner for the transaction to be processed based on the first identification result and the second identification result, the processing manner including releasing the transaction to be processed, or further identifying the risk pertaining to the transaction to be processed via an in-depth identification layer in the risk control system.

According to the second aspect of this application, a risk identification apparatus for transactions to be processed, comprising:

a first identification unit which identifies a risk pertaining to a transaction to be processed via a fast identification layer in the risk control system, thereby obtaining a first identification result;

a second identification unit which identifies a risk of interference pertaining to the

transaction to be processed via a model for identifying transactions susceptible to interference, thereby obtaining a second identification result; and

a determination unit which determines a processing manner for the transactions to be processed based on the first identification result and the second identification result, the processing manner including releasing the transaction to be processed, or further identifying the risk pertaining to the transaction to be processed via an in-depth identification layer in the risk control system.

According to the third aspect of the application, an electronic device for identifying a risk pertaining to a transaction to be processed, comprising:

a processor;

a memory for storing instructions executable by the processor;

wherein, the processor is configured to perform the methods as described in the first aspect.

It can be concluded from the aforesaid technical solution that this application identifies transactions susceptible to interference via a fast identification layer and a model for identifying transactions susceptible to interference before the in-depth identification of the risk control system, thereby identifying transactions susceptible to interference quickly and accurately in the scenario where risks are controllable, and reducing the probability of transactions susceptible to interference being interfered with, as well as reducing the impact on the risk control system and lowering the improvement requirements needed for the risk control system.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a structure diagram of a risk identification system for transactions to be processed provided by an exemplary embodiment;

FIG. 2 is a diagram of a risk control system in the related technologies;

FIG. 3 is a diagram of another risk control system in the related technologies;

FIG. 4 is a flowchart of a risk identification method for transactions to be processed provided by an exemplary embodiment;

FIG. 5 is a diagram of a risk control system provided by an exemplary embodiment in this application;

FIG. 6 is a structure diagram of an electronic device provided by an exemplary embodiment in this application;

FIG. 7 is a flowchart of a risk identification method for transactions to be processed provided by an exemplary embodiment.

DETAILED DESCRIPTION OF EMBODIMENTS

FIG. 1 is a structure diagram of a risk identification system for transactions to be processed provided by an exemplary embodiment. As shown in FIG. 1, the system may include a mobile phone 11, a mobile phone 12 and other user devices, a network 13, and a server 14.

Mobile phones 11-12 are only a type of electronic device usable by users. In fact, the users may apparently also use the following electronic devices: tablet, laptop, pocket PC (PDAs, Personal Digital Assistants), wearable devices (smart glasses, smart watches), etc. which are not limited by this application. When running, the electronic device may run the client program of another application to achieve the relevant transaction functions of the application. For example, the relevant business function may include the transactions to be processed involved in this application, e.g. payment transaction, etc.

Server 14 may include a physical server with dedicated hosting, or the server 14 may be a virtual server hosted on a server cluster, or the server 14 may be a cloud server.

When running, server 14 may load and run the risk control system in this application, thereby achieving the risk control functions and identification functions for transactions susceptible to interference.

For interactive network 13 between mobile phones 11-12 and server 14, multiple types of wired network and wireless network may be included. In an embodiment, the network 13 may include Public Switched Telephone Network (PSTN) and internet. At the same time, electronic devices such as mobile phones 11-12 can also perform communication interaction through network 13, for example, establishing and implementing the transactions to be processed of the present application between any two electronic devices. The risk control system running on server 14 can identify the account theft risk of the transactions to be processed to reduce the probability of the account theft risk evolving into an account theft event.

Based on the identification principles, the risk control system can accurately identify the possible risk issues of the transactions to be processed by using the configured identification rules; here, the identification rules may include manually defined rules or models obtained through machine learning (for example, decision tree-based machine learning or in-depth learning based on neural networks, etc. which are not limited by the present application). Nevertheless, due to the complexity of risk identification, it is often necessary to adopt a large number of identification rules to accurately identify the transaction to be processed; therefore, the identification process not only consumes a large amount of processing computing resources, but also causes operating users to wait for a long time. In fact, as transactions involving account theft risk only account for a small portion and most of the transactions are security events, if it is necessary for all transactions to undergo the processing of the identification rules, this will inevitably lead to the wastage of a large amount of processing computing resources, affect the user

experience of relevant operating users, and even lower the success rate of transaction processing.

Therefore, as shown in FIG. 2, the identification rules of the risk control system are divided into two layers in the related technology: a fast identification layer (also referred to as layer T1) and an in-depth identification layer (also referred to as layer T2). When the risk control system detects the transactions to be processed, layer T1 first identifies the transactions to be processed; layer T1 is configured with fewer fast identification rules (which may include at least one of the various types of the above-described manually defined rules or machine learning models, etc.; which are not limited by the present application), and through these fast identification rules, it is possible to quickly identify transactions to be processed that are security events (there is no or almost no risk of account theft); here, the transactions to be processed will be identified as a security event on layer T1 in most cases and the risk control system will release the transactions to be processed so that the transactions to be processed will continue to be implemented; however, if the transaction to be processed is not identified as a security event, namely, the transaction to be processed is a non-security event in the sense of layer T1 (that is, the transaction to be processed is not an obvious security event, but there may not necessarily be risk of account theft), then the transaction to be processed can be further transferred to layer T2 for identification. Layer T2 is configured with more in-depth identification rules (which may include at least one of the various types of the above-described manually defined rules or machine learning models, etc.; the present application has no limitation on this), and through these in-depth identification rules, it is possible to accurately identify whether the transaction to be processed has a risk of account theft. If layer T2 is identified as a risk-free event, the risk control system will release the transactions to be processed, and if layer T2 identifies a risk event (namely, there is risk of account theft), the risk

control system will perform risk processing on the transaction to be processed, such as by requiring the operating user to perform identification verification, processing failures or restricting the authority of the user account corresponding to the operating user. It can be seen that the above-described division of layer T1 and layer T2 can significantly improve the risk identification efficiency of the transactions to be processed.

Based on the description of the Background section, it can be known that interference may be caused to users when the risk control system is identifying the risk of account theft; to this end, the related technology proposes corresponding improvements to the risk identification process to reduce the probability of “disturbing” users. FIG. 3 is a diagram of another risk control system in the related technology performing identification on transactions susceptible to interference, which means there is a higher probability of the occurrence of the following: the risk control system determines that the transaction is subject to risk of account theft, but the transaction does not actually have this risk (for example, it is judged after the fact that this risk does not exist), thereby causing an “interference” to the corresponding user. As shown in FIG. 3, the related technology follows the “identification rules” originally adopted by the risk control system, and the operator adds rules pertaining to transactions susceptible to interference to the in-depth layer, focusing on the transactions susceptible to interference, the transactions susceptible to interference will be released to avoid “interference”.

Nevertheless, as the rules pertaining to transactions susceptible to interference need to be properly matched with the original identification rules, this makes the configuration process of the rules pertaining to transactions very difficult and may easily make impact on the original identification rules, which not only increase the labor costs of the operator and the maintenance cost of the risk control system, but may even affect the accuracy and efficiency of identifying account theft risk. At the same time, transactions susceptible to

interference are easy to update; for example, when there are new interference user groups or new interference scenarios, etc. These require timely adjustments to the above-described identification rules for interference, thereby further increasing the difficulty and cost of maintaining the risk control system.

In order to solve the above problems in the related technology, the present application proposes further improvements to the risk control system by deviating from the technical ideas of the “identification rules” in the related technology. At layer T1, model for identifying transactions susceptible to interference that is independent to layer T2 is adopted, thereby quickly and accurately identifying transactions susceptible to interference in cases where risk is controllable; moreover, it is easy to implement update processing for model for identifying transactions susceptible to interference, and the maintenance difficulty and maintenance cost of the risk control system can be significantly reduced.

FIG. 4 is a flowchart of a risk identification method for transactions to be processed provided by an exemplary embodiment. As shown in FIG. 4, the method may include the following steps:

Step 402A, risks of transactions to be processed are identified by the fast identification layer in the risk control system to obtain the first identification result.

In the present embodiment, the first identification result is equivalent to the identification result obtained by the risk control system through the fast identification layer of the related technology as shown in FIG. 2. The first identification result can be obtained by the risk control system by applying the fast identification rules to the transactions to be processed.

Step 402B, the second identification result is obtained by identifying interference risks of transactions to be processed through the above-described identification model pertaining to transactions susceptible to interference.

In the present embodiment, in obtaining the first identification result and the second identification result, there is no inevitable sequence between the two.

In the present embodiment, as the fast identification layer adopts far fewer fast identification rules than the number of in-depth rules adopted by the in-depth identification layer, even if there is a certain degree of influence between the model for identifying transactions susceptible to interference and the fast identification rules, the fast identification rules may be optimized based on the lower cost and higher efficiency, thereby reducing the maintenance difficulty and maintenance cost of the risk control system.

In the present embodiment, the model for identifying transactions susceptible to interference may be generated based on positive and negative machine learning samples (which may include various types of machine learning such as decision tree-based machine learning or in-depth learning based on neural networks, etc.; the present application has no limitation on this); wherein positive samples include interfered transactions; negative samples include transactions not interfered that do not actually have pose any actual risk. In the present embodiment, an identification model pertaining to transactions susceptible to interference is generated through the adoption of the manner of machine learning, which may achieve the automatic creation and update of the model for identifying transactions susceptible to interference, exempt or greatly reduce the maintenance costs of the operator for the model for identifying transactions susceptible to interference, and improve the maintenance efficiency of the model for identifying transactions susceptible to interference. Learning from transactions susceptible to interference that have already occurred makes it possible for the model for identifying transactions susceptible to interference to fully grasp the characteristics of transactions susceptible to interference, thereby making it possible to accurately identify transactions susceptible to interference

without creating identification rules pertaining to interference.

In one case, when the model for identifying transactions susceptible to interference is in an initialization state, the above-described positive samples are obtained by weighted sampling of all transactions within a specified historical time period; here, the weighted value of the weighted sample is negatively related to the interval between the sampling time and the time of occurrence of the collected transaction sample, which causes the model for identifying transactions susceptible to interference to comprehensively learn the transactions susceptible to interference while ensuring the model for identifying transactions susceptible to interference is able to adapt to the development and changes of transactions susceptible to interference. For example, the weighting of the positive samples may conform to the following formula: $w_i = e^{-\eta a_i}$, where w_i is the weight corresponding to the i^{th} positive sample, η is the predefined adjustable parameter, and a_i is the time interval corresponding to the i^{th} positive sample. Since the probability of change and degree of change of the negative samples are usually low, the negative samples may be obtained by evenly sampling all the transactions within the specified historical time period.

In another case, when the model for identifying transactions susceptible to interference is a newer model obtained by updating an older model, the positive samples may include at least one of the following: transactions susceptible to interference not identified in the older version model, transactions susceptible to interference identified in the older version model. Here, transactions susceptible to interference not identified in the older version model adapt to the development and changes of transactions susceptible to interference to make the model for identifying transactions susceptible to interference able to learn the latest transactions susceptible to interference; while the transactions susceptible to interference identified in the older version mode inherit the characteristics of the transactions susceptible to interference learnt by the older version model. Here, the

negative samples may be obtained by evenly sampling all the transactions within the time period of the positive samples.

In the present embodiment, the version of model for identifying transactions susceptible to interference may be updated according to a preset period. Since the model for identifying transactions susceptible to interference is obtained through machine learning, the version update process can be automated for high efficiency and minimal maintenance costs.

Step 404, a processing manner for the transactions to be processed is determined based on the first identification result and the second identification result; the processing manner including releasing the transaction to be processed, or further identifying risks pertaining to the transactions to be processed via the in-depth identification layer in the risk control system.

In the present embodiment, values of $f(R,D)$ can be calculated according to the following formula: $f(R,D) = R \cdot I(\beta > R > \alpha) \cdot e^{-D} + I(R \geq \beta)$, where R is the risk score included in the first identification result, D is the interference tendency score included in the second identification result, α and β are preset parameter values and $0 < (\alpha, \beta) < 1$, the value of $I(x)$ is 1 when condition x is satisfied, or is 0 when condition x is not satisfied; when $f(R,D) < \theta$, the processing manner is to release the transaction to be processed; when $\theta < f(R,D) < 1$, the in-depth identification layer of the risk control system further performs risk identification on the transaction to be processed; here, θ is a preset threshold and $0 < \theta < 1$.

For ease of understanding, take the following network platform payment scenario as an example, the technical solution of the present application for the risk control system is applied to the process of identifying the risk of account theft of the payment transaction, and the technical solution of the present application is described in detail in combination with FIG. 5.

FIG 5 is a diagram of a risk control system provided by an exemplary embodiment in this application. As shown in FIG. 5, the risk control system of the present application includes a fast identification layer (namely layer T1) and an in-depth identification layer (namely layer T2); here, layer T2 is the same as layer T2 shown in FIG. 2 and will not be elaborated here.

The present application mainly improves layer T1; as shown in FIG. 5, in the risk control system of the present application, layer T1 is configured with fast identification rules of the relevant technology, an identification model pertaining to payment transactions susceptible to interference, and an integrated decision-making module.

When the risk control system of the relevant technology shown in FIG. 2 improves the risk control system of the present application, it involves an initialization (that is, creation) operation of the identification model pertaining to payment transactions susceptible to interference. The initialization operation can be achieved in the following manner:

Firstly, the risk control system can acquire training samples, which includes positive and negative samples, for initialization of the model. Here, positive sample may be defined as a payment transaction subject to interference that has occurred, namely, a payment transaction that is identified as having the risk of account theft by the risk control system, but is later verified as not having this risk; and negative sample may be defined as a payment transaction that is not identified as having the risk of account theft by the risk control system, and is later verified as not having this risk.

Training samples may be obtained from a specified historical time period, such as payment transactions that occurred in the most recent week. Here, since payment transactions susceptible to interference that count as positive samples account for a relatively small proportion of the total number of payment transactions, this is prone to

violent fluctuations and changes, thus it is possible to obtain the required positive samples from weighted sampling of all payment transactions; moreover, the weighted value of the weighted sample may be negatively related to the interval between the sampling time and the time of occurrence of the collected transaction sample, causing the positive samples closer to the time of sampling to have a greater influence on the training process, thereby allowing the identification model pertaining to payment transactions susceptible to interference obtained from training to adapt to changes in payment transactions susceptible to interference to improve the accuracy of identification of payment transactions susceptible to interference.

For example, the weighting of the positive samples may conform to the following formula:

$$w_i = e^{-\eta a_i},$$

where w_i is the weight corresponding to the i^{th} positive sample, η is the predefined adjustable parameter, and a_i is the time interval corresponding to the i^{th} positive sample.

For negative samples, since the changes of negative samples are usually smaller, the value can be obtained by uniform sampling.

Then, the training samples obtained can be used to train the initialized identification model pertaining to payment transactions susceptible to interference. In the training process, any of the two-class classification algorithms in the related technology can be used for training. The present application has no limitation on this.

Based on the identification model pertaining to payment transactions susceptible to interference obtained via training, identification can be performed on a payment transaction to be processed in the risk control system to obtain an interference tendency score D for the payment transaction to be processed. At the same time, the payment risk score R for the payment transaction to be processed can be obtained according to the fast

identification rules of layer T1, and as shown in FIG. 5, the integrated decision-making module can be used to combine the payment risk score R and the interference tendency score D to determine the processing manner of the payment transaction to be processed.

For example, a decision function $f(R, D)$ may be created, which $f(R, D)$ may be defined as:

$$f(R, D) = R \cdot I(\beta > R > \alpha) \cdot e^{-D} + I(R \geq \beta)$$

where, α, β are preset parameter values and $0 < (\alpha, \beta) < 1$, and the value of $I(x)$ is 1 when condition x is met and 0 when condition x is not met.

Accordingly, by setting a threshold value θ ($0 < \theta < 1$), the processing manner may be determined according to the relationship between the decision function $f(R, D)$ and the threshold θ , e.g.:

1). when $f(R, D) < \theta$, the processing manner is releasing the payment transaction to be processed. Wherein, there may be two scenarios:

Scenario 1: the security level of the payment transaction to be processed is very high so that the payment risk score R meets $R < \alpha$, $f(R, D) = 0$, indicating that the payment transaction to be processed has been determined as secured and can be released directly.

Scenario 2: the payment risk score R meets $\beta > R > \alpha$, indicating that the payment transaction to be processed is subject to payment risks; however, as the payment transaction to be processed is highly likely to be subject to interference, it can thus be determined as a whole that the payment transaction to be processed is susceptible to interference and is released accordingly.

2). When $\theta < f(R, D) \leq 1$, it means that the payment transaction to be processed is subject to certain payment risks and the likelihood of the payment transaction to be processed being subject to interference is low, it can thus be determined that the payment transaction to be processed is not a payment transaction susceptible to interference. The

risks pertaining to the payment transaction to be processed is further identified by the T2 layer in the risk control system.

As described above, in view that the payment transactions susceptible to interference are subject to changes easily, the model for identifying payment transactions susceptible to interference is continuously updated so that it can accurately identify payment transactions susceptible to interference that have changed.

In the technical solution of this application, the model for identifying payment transactions susceptible to interference may be updated periodically, e.g. updated on a daily or weekly basis, the frequency may be set according to the actual circumstances. The update process is similar to the aforesaid initialization process, with the only difference lying in the training samples used.

For positive samples, there can be two sources. Source 1: the interfered payment transactions identified by the old version model (i.e. the to-be-updated model for identifying payment transactions). As the interfered payment transactions are identified by the old version model, so it can be ensured that the new version model will be able to inherit the training results of the old version model, enabling the new version model to identify identical or similar payment transactions susceptible to interference. Source 2: the interfered transactions that occur within the time frame of the positive samples (i.e. the latest 2 days or other time frame), so that the new version model is able to adapt to the update of the payment transactions susceptible to interference; wherein, when the time frame of the positive samples is relatively short, it is fine to use all interfered payment transactions in the time frame of the positive sample; when the time frame of the positive samples is relatively long, and it is fine to sample the interfered payment transactions in the time frame of the positive samples. With respect to the above, references may be made to the aforesaid initialization process.

With respect to negative samples, they may be obtained by evenly sampling the transactions within the time period of the positive samples.

Based on the aforesaid training samples, the binary classification algorithm may be used for the sample training to obtain the latest version model so as to update the model for identifying payment transactions susceptible to interference.

It can be concluded from the aforesaid technical solution that this application identifies transactions susceptible to interference via a fast identification layer and identification model for transactions susceptible to interference before the in-depth identification of the risk control system, thereby identifying transactions susceptible to interference quickly and accurately in the scenario where risks are controllable, and reducing the probability of transactions susceptible to interference being interfered, as well as reducing the impact on the risk control system and lowering the improvement requirements needed for the risk control system.

FIG. 6 is a structure diagram of an electronic device provided by an exemplary embodiment in this application; As shown in FIG. 6, at hardware level, the electronic device includes a processor 602, an internal bus 604, a network interface 606, an internal memory 608 and a nonvolatile memory (NVM) 610. Of course, it may further include other hardware needed for transactions. The processor 602 reads a corresponding computer program from the NVM 610 to the internal memory 608 and then runs the computer program to form a terminal interaction apparatus at a logical level. Of course, in addition to the software implementation manner, the present application does not exclude other implementation manners, such as a logic device or a combination of software and hardware. That is to say, the executive bodies of the following processing flow are not limited to logical units and may be hardware or logic devices too.

Refer to FIG. 7, in the software implementation manner, the risk identification

apparatus for transactions to be processed may include:

the first identification unit 71 for identifying risks pertaining to transactions to be processed via a fast identification layer in the risk control system, thereby obtaining the first identification result;

the second identification unit 72, which identifies the risks of interference pertaining to the transaction to be processed via a model for identifying transactions susceptible to interference, thereby obtaining the second identification result;

a determination unit 73 which determines the processing manner for the transactions to be processed based on the first identification result and the second identification result; the processing manner including releasing the transaction to be processed, or further identifying risks pertaining to the transactions to be processed via the in-depth identification layer in the risk control system.

Optionally, the model for identifying transactions susceptible to interference is generated by way of machine learning based on positive samples and negative samples; the positive samples including: interfered transactions; the negative samples including un-interfered transactions that are subject to no risks.

Optionally, when the model for identifying transactions susceptible to interference is in an initial state, the positive samples are obtained by weighted sampling all transactions in a specified historical period; wherein the weight of weighted sampling is negatively correlated to the interval between the sampling time and the time of the sampled transactions.

Optionally, the weight of positive samples complies with the following formula:

$$w_i = e^{-\eta a_i}$$

where w_i is the weight of the i^{th} positive sample, η is the predefined adjustable parameter, a_i is the interval of the i^{th} positive sample.

Optionally, the negative samples are obtained by evenly sampling in all transactions within a specified historical period.

Optionally, when the model for identifying transactions susceptible to interference is a newer version model obtained by updating an older version model, the positive sample may include at least one of the following: transactions susceptible to interference not identified in the older version model, transactions susceptible to interference identified in the older version model.

Optionally, the negative samples are obtained by uniformly sampling all the transactions within the time period of the positive samples.

Optionally, the version of the model for identifying transactions susceptible to interference is updated according to a preset period.

Optionally, the determination unit 73 is used for:

calculating the score of decision function $f(R, D)$ according to the following formula: $f(R, D) = R \cdot I(\beta > R > \alpha) \cdot e^{-D} + I(R \geq \beta)$; where R is the risk score included in the first identification result, D is the interference tendency score included in the second identification result, α and β are preset values and $0 < (\alpha, \beta) < 1$, the value of $I(x)$ is 1 when condition x is met and 0 when condition x is not met.

Where $f(R, D) < \theta$, the processing manner is releasing the transaction to be processed; where $\theta < f(R, D) \leq 1$, the in-depth identification layer in the risk control system further identifies risks in the transaction to be processed; wherein θ is the preset threshold value, and $0 < \theta < 1$.

The electronic devices, apparatuses, modules or units illustrated in the above-described embodiments may be achieved by computer chips or entities, or by products with certain functions. A typical achievement device is a computer. An exemplary form of the computer may be a personal computer, laptop computer, cell phone, camera phone,

smart phone, PDA (personal digital assistant), media player, navigation device, email sending and receiving device, game console, tablet computer, wearable device or any combination of a few of these devices.

In a typical configuration, the computer includes one or more processors (CPUs), I/O interfaces, network interfaces and internal memories.

The internal memory may be in a form of volatile memory, random access memory (RAM) and/or non-volatile memory such as read-only memory (ROM) or flash memory (flash RAM) in the computer readable media. Internal memory is an example of computer readable media.

Computer readable media include non-volatile and volatile and movable and non-movable media, and information storage may be achieved by any method or technology. Information could be computer readable instructions, data structures, program modules or other data. Examples of computer storage media include but are not limited to phase change random access memory (PRAM), static random access memory (SRAM), dynamic random access memory (DRAM) and other types of random access memory (RAM), read only memory (ROM), electrically erasable programmable read only memory (EEPROM), flash memory or other memory technologies, compact disc – read only memory (CD-ROM), digital versatile disc (DVD) or other optical memory, cassette type magnetic tape, magnetic disk memory, magnetic tape, magnetic disc storage or other magnetic storage devices or any other non-transmission media. They may be used to store information that is accessible to computer devices. According to the definition in this document, computer readable media do not include transitory media, such as modulated data signals and carriers.

It should be further noted that terms “include,” “comprise” or any variants of these terms are intended to cover non-exclusive inclusion so that a process, method, article or

equipment including a series of elements not only includes these elements but also includes other elements that are not expressly listed, or also includes the elements inherent to such process, method, article or equipment. In the absence of more limitations, the elements defined by a sentence “include one.....” do not exclude that the process, method, article or equipment including the elements also have other same elements.

Here, exemplary embodiments will be described in detail, with examples shown in the accompanying drawings. When the description below involves the accompanying drawings, unless otherwise indicated, the same numeral in different accompanying drawings stands for the same or similar element. The implementation manners described in the following exemplary embodiments do not represent all the implementation manners consistent with the present application. Conversely, they are merely examples of the apparatus and method described in detail in the attached claims and are consistent with some aspects of the present application.

The terms used in the present application are merely for the purpose of describing certain embodiments, instead of limiting the present application. The singular forms “a,” “the” and “this” used in the description and in the attached claims also are intended to cover plural forms unless their meanings are otherwise clearly indicated in the context. It should also be understood that the term “and/or” used in the text refers to any or all possible combinations containing one or more of the associated listed items.

It should be understood that although the present application may use terms such as first, second and third to describe various kinds of information, the information should not be limited to these terms. These terms are only intended to differentiate information of the same type. For example, without departing from the scope of the present application, first information may also be referred to as second information, and similarly, second information may also be referred to as first information. Subject to the context, the term

“if” used here may be interpreted as “at the time of ...,” “when,” or “in response to a determination.”

The above embodiments are merely preferred embodiments of the present application but not intended to limit the present application. All modifications, identical replacements and improvements made without departing from the spirit and principle of the present application shall fall within the scope of the present description.

Claims

1. A method for identifying a risk pertaining to a transaction to be processed, comprising:

identifying a risk pertaining to a transaction to be processed via a fast identification layer in a risk control system, thereby obtaining a first identification result;

identifying a risk of interference pertaining to the transaction to be processed via a model for identifying transactions susceptible to interference, thereby obtaining a second identification result, wherein the model for identifying transactions susceptible to interference is generated by way of machine learning based on positive samples and negative samples, the positive samples including interfered transactions, the negative samples including un-interfered transactions that are subject to no risks, and wherein when the model for identifying transactions susceptible to interference is in an initial state, the positive samples are obtained by weighted sampling all transactions in a specified historical period, a weight of weighted sampling being negatively correlated to an interval between a sampling time and a time of a sampled transaction; and

determining a processing manner for the transaction to be processed based on the first identification result and the second identification result, the processing manner including releasing the transaction to be processed, or further identifying the risk pertaining to the transaction to be processed via an in-depth identification layer in the risk control system.

2. The method according to claim 1, wherein the weight of positive samples complies with the following formula:

$$w_i = e^{-\eta \alpha_i}$$

where w_i is the weight of an i^{th} positive sample, η is a predefined adjustable

parameter, and a_i is an interval of the i^{th} positive sample.

3. The method according to claim 1, wherein the negative samples are obtained by evenly sampling in all transactions within the specified historical period.

4. The method according to claim 1, wherein when the model for identifying transactions susceptible to interference is a newer version model obtained by updating an older version model, the positive samples comprise at least one of the following: interfered transactions not identified in the older version model, interfered transactions identified in the older version model.

5. The method according to claim 4, the negative samples are obtained by evenly sampling in all transactions within a period in which the positive samples are.

6. The method according to claim 1, wherein a version of the model for identifying transactions susceptible to interference is updated according to a preset period.

7. The method according to claim 1, wherein determining the processing manner of the transaction to be processed based on the first identification result and the second identification result comprises:

calculating a score of a decision function $f(R, D)$ according to the following formula:

$f(R, D) = R \cdot I(\beta > R > \alpha) \cdot e^{-D} + I(R \geq \beta)$, where R is a risk score included in the first identification result, D is an interference tendency score included in the second identification result, α and β are preset values and $0 < (\alpha, \beta) < 1$, a value of $I(x)$ is 1 when condition x is met and 0 when condition x is not met;

when $f(R, D) < \theta$, the processing manner is releasing the transaction to be processed, and when $\theta < f(R, D) \leq 1$, the in-depth identification layer in the risk control system further identifies the risk pertaining to the transaction to be processed; wherein θ is a preset threshold value, and $0 < \theta < 1$.

8. An apparatus for identifying a risk pertaining to a transaction to be processed, comprising:

a first identification unit which identifies a risk pertaining to a transaction to be processed via a fast identification layer in a risk control system, thereby obtaining a first identification result;

a second identification unit which identifies a risk of interference pertaining to the transaction to be processed via a model for identifying transactions susceptible to interference, thereby obtaining a second identification result, wherein the model for identifying transactions susceptible to interference is generated by way of machine learning based on positive samples and negative samples, the positive samples including interfered transactions, the negative samples including un-interfered transactions that are subject to no risks, and wherein when the model for identifying transactions susceptible to interference is in an initial state, the positive samples are obtained by weighted sampling all transactions in a specified historical period, a weight of weighted sampling being negatively correlated to an interval between a sampling time and a time of a sampled transaction; and

a determination unit which determines a processing manner for the transaction to be processed based on the first identification result and the second identification result, the processing manner including releasing the transaction to be processed, or further identifying the risk pertaining to the transaction to be processed via an in-depth

identification layer in the risk control system.

9. The apparatus according to claim 8, wherein the weight of positive samples complies with the following formula:

$$w_i = e^{-\eta a_i}$$

where w_i is the weight of an i^{th} positive sample, η is a predefined adjustable parameter, and a_i is an interval of the i^{th} positive sample.

10. The apparatus according to claim 8, wherein the negative samples are obtained by evenly sampling in all transactions within a specified historical period.

11. The apparatus according to claim 8, wherein when the model for identifying transactions susceptible to interference is a newer version model obtained by updating an older version model, the positive samples include at least one of the following: interfered transactions not identified in the older version model, interfered transactions identified in the older version model.

12. The apparatus according to claim 11, wherein the negative samples are obtained by evenly sampling in all transactions within a period in which the positive samples are.

13. The apparatus according to claim 8, wherein a version of the model for identifying transactions susceptible to interference is updated according to a preset period.

14. The apparatus according to claim 8, wherein the determination unit is used for: calculating a score of a decision function $f(R, D)$ according to the following formula:

$f(R,D) = R \cdot I(\beta > R > \alpha) \cdot e^{-D} + I(R \geq \beta)$, where R is a risk score included in the first identification result, D is an interference tendency score included in the second identification result, α and β are preset values and $0 < (\alpha, \beta) < 1$, the value of $I(x)$ is 1 when condition x is met and 0 when condition x is not met;

when $f(R, D) < \theta$, the processing manner is releasing the transaction to be processed, and when $\theta < f(R,D) \leq 1$, the in-depth identification layer in the risk control system further identifies the risk pertaining to the transaction to be processed, wherein θ is a preset threshold value, and $0 < \theta < 1$.

15. An electronic device, comprising:

a processor;

a memory for storing instructions executable by the processor;

wherein the processor is configured to perform the method according to any of claims 1-7.