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Intelligent Anti-Money Laundering System for Money Service Business

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Abstract: The criminal individuals and organizations in today's world including terrorists have taken advantage of the available financial systems, to launder money from illegal proceeds and for their illegal activities. India is particularly under threat from terrorists and it also has been difficult to track down the finance of criminal elements. Developing effective suspicious activity detection models has drawn more and more interests for supervision agencies and financial institutions in their efforts to combat money laundering.

This paper proposes a suspicious activity recognition method basing on scan statistics; it aims to identify suspicious sequences on transaction level for financial institutions. In order for a more adaptive, intelligent and flexible solution for anti-money laundering, the intelligent agent technology is applied in this research. Several types of agents are proposed and multi-agent architecture is presented for anti-money laundering. A prototype system for money laundering detection is also developed to demonstrate the advances of the proposed system architecture and business value.

Keywords— Anti-money laundering, Intelligent agents, suspicious activity.

I. INTRODUCTION

Money laundering (ML) is a process to make illegitimate income appear legitimate; this is also the process by which criminals attempt to conceal the true origin and ownership of the proceeds of their criminal activity. Through money laundering, criminals try to convert monetary proceeds derived from illicit activities into “clean” funds using a legal medium such as large investment funds hosted in investment Since the mid-1980s, money laundering (ML) has been increasingly recognized as a significant global problem, with serious economic and social ramifications. Today, ML has become a key funding mechanism for international religious extremism and drug trafficking, and curtailing. These illegal activities has become an important focus of governments as part of their ongoing wars on terrorism and drug abuse. Following the terrorist activity of September 11, 2001, there has been an increased focus in the United States and across the globe on the prevention of ML and terrorist financing.

Increasingly, anti-money laundering (AML) systems are implemented to combat ML. the financial institutions, reporting suspicious activity reports (SARs) is of most importance in their AML work due to the following reasons [1]

1) It generates an initial set of potential money laundering cases for financial supervision agencies in further investigation.
2) It is helpful in summarizing money laundering trends and patterns so that those similar money laundering cases can be prevented .
3) Data from AML experts showed that about 90% money laundering cases were found though SARs; only 10% cases were identified starting from large value reports .

II. BACKGROUND

A. *Money Laundering*

Money laundering (ML) is a term usually used to describe the ways in which criminals process illegal or "dirty" money derived from the proceeds of any illegal activity (e.g. the proceeds of drug-dealing, human trafficking, fraud, theft or tax evasion) through a succession and deals until the source of illegally acquired funds is obscured and the money takes on the appearance of legitimate or "clean" funds or assets . ML is a diverse and often complex process that need not involve cash transactions. ML basically involves three independent steps [2] that can occur simultaneously :

* Placement - the process of transferring the proceeds from illegal activities into the financial system in such a manner as to avoid detection by financial institutions and government authorities.

* Layering - the process of generating a series or layers of transactions to distance the proceeds from
their illegal source and obscure the audit trail.

* Integration - the unnoticed reinsertion of successfully laundered, untraceable proceeds into an economy.

B. *Anti-Money Laundering Systems*

In an effort to detect potential ML schemes, many financial institutions have deployed AML detection solutions and enterprise-wide procedural programs. The solutions worked by establishing fixed rule-based thresholds by analyzing how certain established usage scenarios comply within those boundaries. Most financial institutions will establish a threshold based on a set monetary value for each transaction and detecting specific ML patterns and user scenarios that breached those thresholds. The shortcomings associated with those solutions are summarized as follows:[4]
* Those solutions have an inherent inability to detect ML schemes of smaller amounts that may come in under a defined threshold limit.
* Problem of false positive, which means there are transactions over a set limit that are marked as suspicious but that do not represent any existing identified risk to the institution.
* Although those rule-based systems have some pattern recognition capabilities, they do not have learning or generalization abilities and can only match patterns that they already know.

III. INTELLIGENT AGENTS

The development of intelligent agents (IAs) and multi-agent systems (MASs) has recently gained popularity among IS researchers [8]. Although there is no universally accepted definition of the term "agent," and indeed there is a good deal of ongoing debate and controversy on this very subject, the central point of agents is that they are autonomous: capable of acting independently, exhibiting control over their internal state. Wooldridge and Jennings suggest a precise description of agents; one that may be widely adopted in artificial intelligence communities as well as general computing areas. An agent [3] is defined as a computer system that is situated in some environment, and is capable of autonomous action in that environment in order to meet its design objectives [9]. Furthermore, agents are able to act without the intervention of humans or other systems: they have control both over their own internal state, and over their behavior [10]. An intelligent agent (IA) is one that is capable of flexible autonomous action in order to meet its design objectives, where flexibility includes properties such as autonomy, social capability, reactivity, and pro activity. A generic agent has a set of goals, certain capabilities to perform tasks, and some knowledge about its environment. proposed to design and develop numerous intelligent-agents based business systems . The main benefits of an agent-based approach come from its flexibility, adaptability, and decentralization.

To achieve its goals, an agent needs to use its knowledge to reason about its environment and the behaviors of other agents, to generate plans and to execute these plans.
A M\AS consists of a group of agents, interacting with one another to collectively achieve their goals. By absorbing other agents' knowledge and capabilities, agents can overcome their inherent bounds of intelligence . One of the current factors (and arguably one of the more important ones) fostering M\AS development is the increasing popularity of the Internet, which provides the basis for an open environment where agents interact with each other to reach their individual or shared goals.

In recent years, there has been considerable growth of interest in the design of a distributed, intelligent society of agents capable of dealing with complex problems and vast amounts of information collaboratively. Since agent technology provides flexible, distributed, and intelligent solutions for business applications, researchers have proposed to design and develop numerous intelligent-agents based business systems . The main benefits of an agent-based approach come from its flexibility, adaptability, and decentralization.

1. Deployment of Intelligent Agents

Besides being complex, AML is also a kind of collaboration process, in which multiple organizations and a mixture of human activities and automated tasks are involved. In order to design the architecture of a multi-agent AML solution, we decomposed the process of AML into several autonomous phases [4], in which each agent is delegated a particular task to exhibit its goal-oriented and reactive behavior, and cooperate with others to pursue their goals. The process of AML usually consists of the phases of data collecting, ML risk monitoring, behavior diagnosing, and suspicious activity reporting. Furthermore, data collecting involves internal and external data collection; while ML monitoring is composed of client profile assessment and transaction risk measurement. Accordingly, the taxonomy of intelligent agent for AML is outlined in Figure 1, in which several intelligent agent classes are applied to provide a set of AML functionalities for existing financial institutions. The details of these agents are described in the following subsection. Figure 1. Agent hierarchy for anti-money laundering

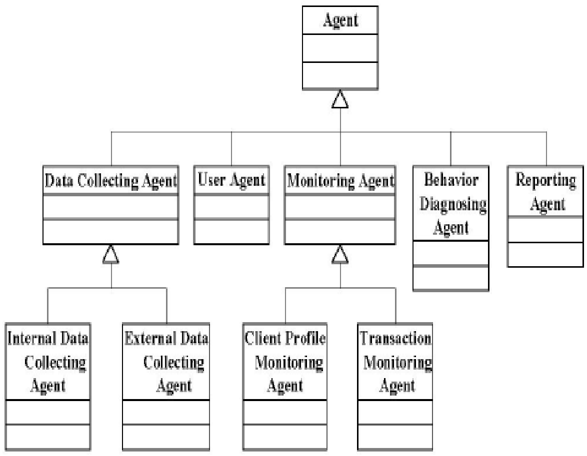
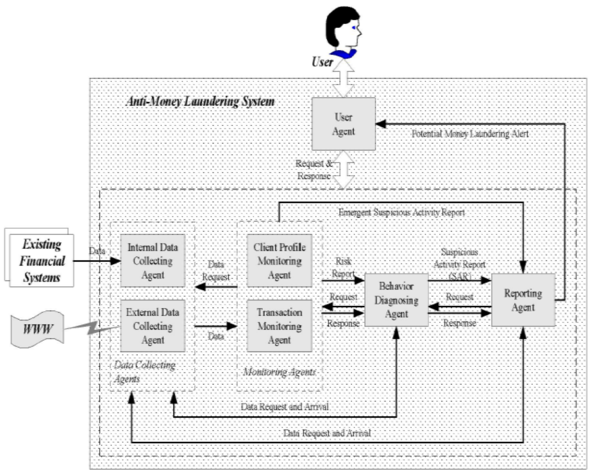


FIG 1

2. *System Architecture*

The existing financial systems are distributed in various institutions, e.g., Money Service Business, banks, insurance companies, security trading firms. Our work is to fundamentally use internal resources to build software capabilities to interact with legacy systems. Based on the analysis above and the deployment of intelligent agents in the previous subsection, the architecture of the IAMLS is portrayed in Figure 2, which describes the internal interactions among agents and the external relationship between the IAMLS and existing financial systems. The agents are distributed in financial organizations or departments involved in AML[5] ; they communicate each other through the Internet. As related before, all these agents work autonomously and collaboratively in the multi-agent environment. Each Agent focus on its particular task



without inventions from outside. And by drawing on other agents' knowledge and capabilities, agents can overcome their inherent bounds of intelligence and work collaboratively to pursue their goals.

- The User Agent [7] enables users to view the current state of the financial transactions and ML monitoring, diagnosing, and reporting processes and allows them to convey their own judgments, opinions, and arguments relative to ML detection to the rest of financial institution.
- The Data Collecting Agents enable the system to collect data internally and externally.
- The Monitoring Agents, Diagnosing Agent, and Reporting Agent may request data relating to their task from the Data Collecting Agents, if required. Two kinds of Monitoring Agents include Client Profile Monitoring Agent and Transaction Monitoring Agent .
- The Client Profile Monitoring Agent is to assess a wide variety of detailed information relating to the client's account, typically collected at the time that the account is opened.
- The Transaction Monitoring Agent is to identify transactions that pose the greatest risk for potential ML activities.
- When the Behavior Diagnosing Agent identified unusual or suspicious behavior, a suspicious activity report (SAR) will be automatically produced and sent to the Reporting Agent (RA). Then the RA will present and communicate a potential ML alert to the appropriate compliance personnel through the User Agent for case management investigation and action.

3. *System Operation*

In order to evaluate our architectural design, a prototype has been implemented. [13] The prototype system carries out the analysis, monitoring, diagnosing, and reporting using simulated client profile and financial transaction data based on a small number of intelligent agents. Within our prototype, the Data Collecting Agents continuously collect relevant simulated client and transaction data in real time, automatically response to any data request from other agents in a timely manner. The Monitoring Agents and Behavior Diagnosing Agent are pre-configured with detailed ML scenarios. These scenarios are patterns of behavior that are of interest to the organization and based on the Regulator's compliance rules (e.g., FATF 40 Recommendations). The scenarios are adaptable and can easily be extended. The agents have the flexibility to allow the organizations to incorporate their own specific business scenarios reflecting their security practices. In addition, various advanced techniques are combined into a holistic, risk-based approach. By evaluating other risk factors, the most relevant alerts are raised. With a risk-based approach, a combination of rules, anomaly detection, neutral network, fuzzy logic, linear programming are employed and assigned a risk weighting. For each scenario, scores are assigned to each risk factor, and then multiplied by the risk weighting to get the overall scores. By so doing, financial organization is able to more effectively evaluate the subtle patterns of ML in the context of other existing risk attributes. When dealing with previously unseen patterns, these agents are able to remember the patterns, for future reference, and make generalization about them. In this way, they can adapt to different inputs and produce findings on both previously seen and previously unseen patterns. The User Agent provides the interface to the user, who may be a ML analyst. It communicates and cooperates with other agents, automatically executes its operation, and gives different response to environmental changes. The User Agent is instructed by the user during initialization to start the data simulation and the autonomous monitoring and diagnosing activities. Subsequently, the agents perform their tasks continuously and accurately until the user asks them to stop or change their goal. The following suspicious ML scheme [15] example illustrates how our prototype works. Three months of simulated banking transaction data shows deposits were made daily to a foreign currency account totaling about US$350,000. In the same period of time, there are 10 wire transfers totaling US$2.7 million to a bank in the United Arab Emirates. These unusual activities are captured by the Transaction Monitoring Agent and are forwarded to the Behavior Diagnosing Agent by a risk report. In order to investigate this case, the Behavior Diagnosing Agent request client profile analysis from the Client Profile Monitoring Agent, source and destination account information and transaction details from the Transaction Monitoring Agent, and related additional data from the External Data Collecting Agent. After the [14] risk-based analysis, three alerts with reasoning were given by the prototype: the first one is "Relationship with terrorism," since company profile shows most of the transactions of this company were conducted by countries associated with terrorist activities (e.g., United Arab Emirates, which is identified as a high risk country). The second alert is "The company was involved with several drug transactions occurred in Colombia," it is because based on the findings of the Drug Enforcement Administration and the bank records, the company was always receiving money from accounts owned by Columbia organizations. The third one is [12] "Unclear source of a large amount of money," where no materials showed how money is earned from its business, only records indicated that the company received money from individual accounts of other countries or Columbia companies or banks.

IV. CONCLUSION

This paper explores the approach of applying intelligent agents for money laundering prevention controls to overcome the limitations of existing anti-money laundering (AML) solutions. A novel and open multi-agent-based AML system is designed and implemented, in which various classes of intelligent agents are proposed to provide a set of functionalities for AML. In sum, our approach has several [11] advantages for AML:

- Intelligence: Complex and distributed ML schemes can be identified and diagnosed by a number of intelligent agents through their properties, such as autonomy, reactivity, pro-activity, and social ability.
- Adaptivity: Our system can not only perform autonomous monitoring and diagnosing work, but also be able to learn from its environment, adapt to changes in the environment and to make decisions that can then be delivered to and interpreted by human eyes.
- System integration: Through the User Agent, our intelligent AML system is able to easily integrate with legacy financial application.
- Scalability: It is easy to add more business functionalities into our system by adding more agents. It is also simple to modify, insert, or delete business rules or ML scenarios in the system.
- Business values: Our approach can offer significant business benefits in terms of reduced costs, business efficiencies, increased productivity and new style of operation.

By following the architecture, we will conduct further task analysis and knowledge acquisition on the prototype system. The system effectiveness will also be evaluated in the future

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