Distributed Learning of Information Fusion: A Multi-agent Approach

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Abstract - *An important task of information fusion scope is learning of decision making and decision combining. This task that falls under Distributed Learning scope is a subject of the paper. It is supposed that distributed learning is carried out by a component of information fusion system performing supervised off-line training and testing of its decision making component. The core problem of a distributed learning component design does not concern particular data mining techniques. Instead of this, its core problem is development of an infrastructure and protocols supporting coherent collaborative operations of distributed software components (agents) responsible for distributed learning. The paper is focused on architecture of multi-agent information fusion systems possessing learning capabilities, on a technology supported by a software tool and on protocols of software tool agents' interaction, particularly, distributed data mining protocol. Solutions concerning the aforementioned aspects form the basis for the multi-agent information fusion system technology and respective software tool.*

Key words: Information fusion, multi-agent system, software tool, distributed data mining, interaction protocols, situational awareness.

1 Introduction

Information fusion (IF) is a task of data and information processing aiming at making decisions on the basis of distributed heterogeneous data and information sources specifying an object state, a situation constituted by autonomous interacting objects, intent of a situation management to achieve, etc [15]. Formally, *decision making* in an IF system is understood as *classification*.

Distributed data and information used for producing decisions in an IF system can be of different physical nature (images, sensor's data, experts' information, etc.), be of different accuracy and reliability. Particular data may be incomplete, uncertain and be represented in different data structures. The most specific peculiarity of IF task is that each particular information source is capable to provide only *partial awareness.* The objective of IF is to provide whole understanding of a situation called *situational awareness*.

Recent publications proved that now the area of IF applications is increasingly growing and becoming a critical technology. To make it clear what applications the paper is referred to, let us outline two of them.

1. Detection of intrusions into computer network [1]. At present coordinated distributed attacks performed by a team of malefactors from spatially distributed hosts constitute the main threats for computer networks and information. "Traces" of an attack proves in different data perceived or generated by a computer network assurance system. For example, they are displayed in IP packets of input traffic, in *tcpdump* generated via input traffic preprocessing, in audit data trail, in sequences of system calls of operating system, in data resulting from monitoring of application servers, queries to databases and directories, in data specifying users' profiles, etc. Such data are generated on different hosts of computer network. The timely detection of an illegitimate user's activity is potentially feasible only in case of fusion information obtained from different sources. Formally, intrusion detection is a classification task which makes global decision on the basis of combining particular decisions produced on the basis of many sources.♦

2. Analysis and prognosis of natural and man-made disaster development. A lot of different kinds of potentially dangerous situations emerge in different regions of many countries. They can emerge due to natural disasters (earthquakes, floods, etc.), man-caused emergencies (chemical, nuclear, etc.) and so on. The specific features of such phenomena are rapid and weakly predictable development in time and space, strong dependence on weather conditions, landscape, buildings infrastructure and so on. To assess the whole situation in order to predict its development and to prevent its undesirable or catastrophic consequences, it is necessary to use data and information from different sources. The sources of such data and information can specify weather conditions, information collected by airborne equipment (photo, TV, infrared, etc), people's messages, simulation data, and so on. ♦

There exist many other applications in different areas that fall into common scope called *situational awareness*.

The IF research area is actually challenging and puts a number of specific problems. The most important ones result from the distributed nature of decision making and learning of distributed decision making. Indeed, according to the recent understanding IF has to be designed as a collection of distributed program (in our technology–software agents) interacting to produce decision in a cooperative way. This task requires development of specific protocols (distributed algorithms) needed to coordinate distributed parallel processes of decision making in an IF system. On the other hand, Distributed Learning (DL) component aiming at training and testing of IF system is also to be distributed and its components, training and testing software agents, also have to operate according to a number of protocols. Finally, if to analyze IF system technology and supporting software tool then one can arrive to a conclusion that the aforementioned software has also to be distributed.

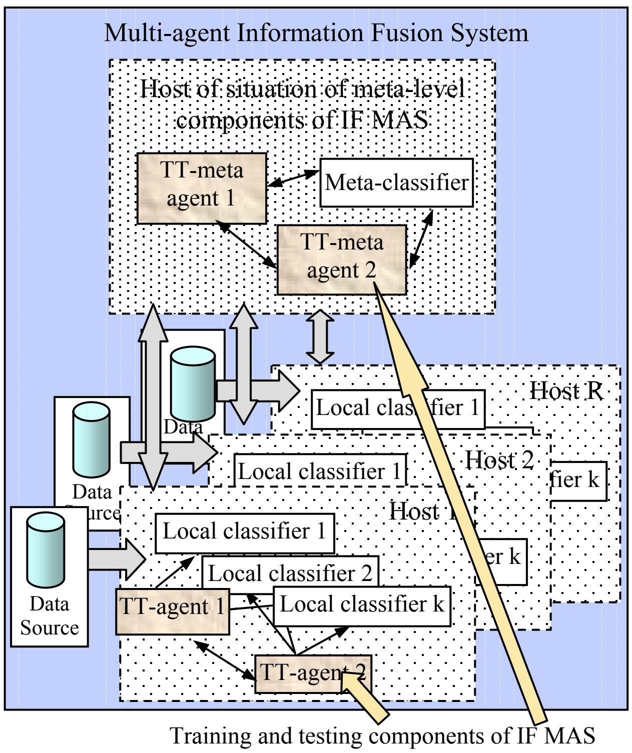

Figure 1. General view of IF MAS architecture

The paper is focused on several challenges of the multi-agent IF system design. In particular, it outlines the developed technology, presents architecture of the respective software tool and describes basic protocol supporting distributed IF system design and distributed training and testing of IF system in order to make it able to realize procedure leading from *distributed information* through *distributed awareness* to *situational awareness*.

The rest of the paper is organized as follows. In *section 2* we present general view of IF system architecture. In *section 3* the used IF technology is briefly presented. *Section 4* conceptually outlines peculiarities of distributed ontology design. *Section 5* describes the meta-model of IF. *Section 6* presents the key ideas of distributed data mining (DDM) for training of IF systems and describes a key protocol, DDM protocol. *Section 7* gives brief information concerning case studies have been used for validation of the developed IF technology. *Conclusion* summarizes the main results and future work.

2 IF System Architecture

In our development we consider multi-agent architecture of IF system. It comprises two types of agent-based components (Figure 1). The first of them corresponds to the components that operate with the source-based information and situated at the same hosts as sources. The second component operates with the meta-information generated on the basis of source-based information and can be situated at any host. Each component includes classification agents (local and meta-level respectively) and training and testing agents (TT-agents) responsible for providing the IF system for learning capabilities.

A more detailed architecture of the multi-agent information fusion system is presented in Figure 2 and Figure 3. The former depicts architecture of source-based components of IF multi-agent system (MAS) and the latter depicts architecture of its meta-level component.

The functionalities of source-based component of IF multi-agent system (Figure 2) are as follows:

Data source managing agent

- Participates in the distributed design of the consistent shared component of the application ontology;
- Collaborates with meta-level agents in management of training and testing of particular source-based classifiers and in forming meta-data sample for meta-level training and testing;
- Supports gateway to databases performing transformation of queries from the language used in ontology into SQL language.

KDD agent of data source

- Trains and tests of source-based classification agents and assesses of designed classifier' quality.

Classification agents of data source

- Produce decisions using source-based information. They are subjects of training performed by TT-agents.

Server of learning method (not an agent)

- This component comprises a multitude of classes implementing KDD methods, quality metrics, etc.

The functionalities of meta-level component of IF multi-agent system (Figure 3) are as follows:

Meta-Learning agent ("KDD Master")-TT-agent

- Manages the distributed design of IF system application ontology,
- Computes the training and testing meta-data sample, manages design of meta-model of decision making.

Information Fusion management agent

- coordinates performance of *Agent-classifier of meta-level* and *Meta-level KDD agent* both in training and decision fusion modes of performance.

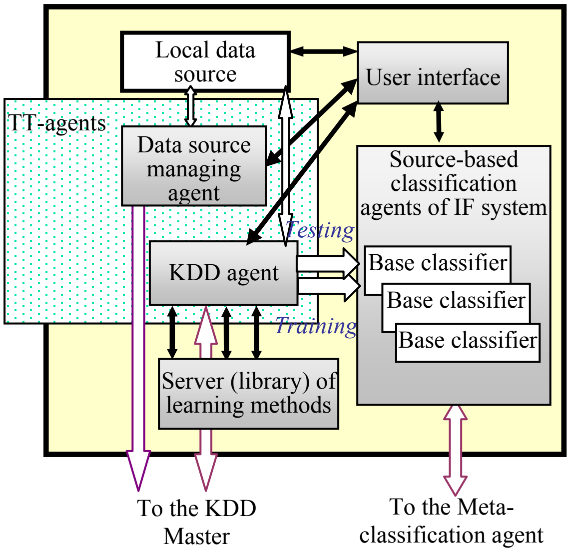

Figure 2. Architecture of source-based component IF MAS

*Server (library) of KDD methods (*not an agent)

- This component comprises a multitude of classes implementing KDD methods, quality metrics, etc.

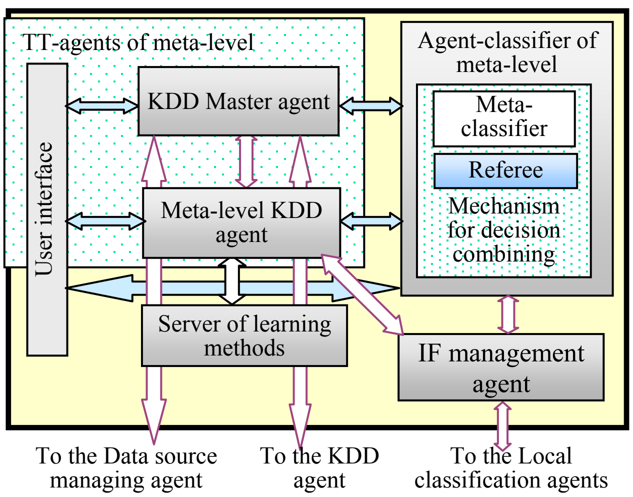

Figure 3. Architecture of meta-level component of IF MAS

3 Technology of IF Systems Design

The developed technology for IF MAS system design and implementation is based on using of special technology framework supported by a software tool [7]. The basic idea of this technology framework is as follows. At start up point the developer has available so-called *Generic multi-agent system*, a number of protocols, library of training and testing methods and user interface.

Generic multi-agent system is designed through use of Multi-Agent System Development Kit, MASDK [7], that is software tool of general purposes for the design and implementation of wide class of MAS. *Generic multi-agent system* comprises agents supposed by the developed architecture (Figure 2, 3) and communication environment, but its agents are only provided by reusable functionalities. It is reasonable to call these agents as "empty" ones.

The protocols, library of training and testing methods, and user interface aim to "fill in" the "empty" agents in order to specialize *Generic multi-agent system* in interactive and iterative mode, to specialize its communication component and deploy the resulting IF MAS in a computer network.

Figure 4 explains the hierarchy of users' activities within the aforementioned technology framework. In this hierarchy, *Generic multi-agent system* corresponds to the initial software framework that is "step-by-step" transformed into IF MAS provided of learning capabilities. At that, the design procedure is performed by users that communicate with the technology framework through user interface, perform design according to a number of protocols supporting distributed design mode, and also use the library of training and testing methods needed for IF system learning on the basis of the respective training and testing datasets.

High-level protocol of IF system design, in which training of IF MAS is the core procedure, is given in Figure 5 in terms of standard IDEFO diagrams. It comprises a number of processes (sub-protocols) that are:

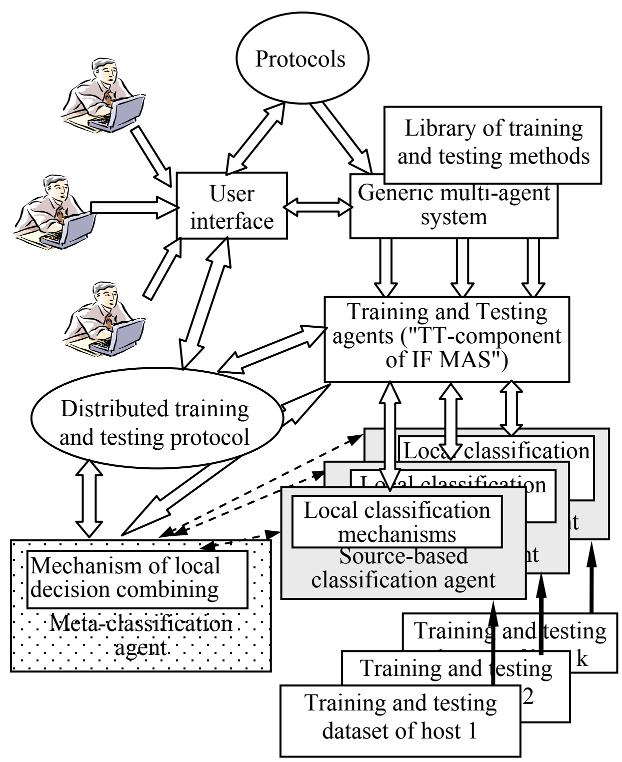

Figure 4. Explanation of the technology framework used for the design of IF MAS

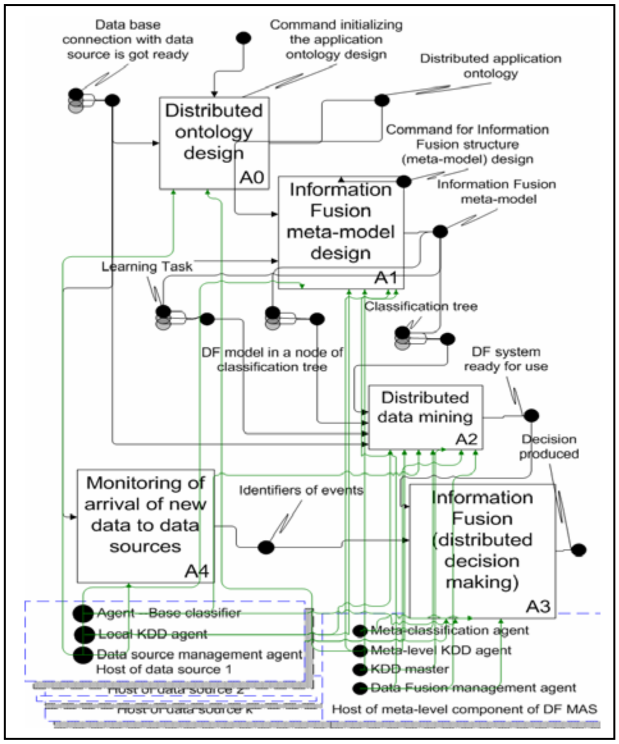

Figure 5. High-level protocol of IF system design

A0. Distributed ontology design.
A1. IF meta-model design.
A2. Distributed data mining.
A4. Monitoring of arrival of new data to data sources.
A5. Information Fusion (Distributed decision making).

This diagram specifies interaction of agents, intermediate and final results and activity processes ordering.

The core protocols of the technology are those providing IF system of learning capabilities that are A0, A1 and A2 protocols. They are explained below.

4 Distributed ontology design

The key IF peculiarities come out of the fact that information sources are *distributed* and *heterogeneous*. As a rule, information is also of large scale. Distribution, heterogeneity and large scale of information put problems strongly influencing on many issues of IF system design. Use of *ontology* is now considered as the only approach to cope with the data distribution and heterogeneity problem. In high-level protocol of IF system learning (Figure 5) the design of ontology is considered as the first step.

The main distinction of the ontology supporting for IF system performance is that it is distributed and has also to be designed in distributed way. Conceptually the process of distributed ontology design is explained in Figure 6. It is conducted according to the protocol indicated in Figure 5.

Several problems are resolved on the basis of use of ontology [6]. The *first* of them is development of the

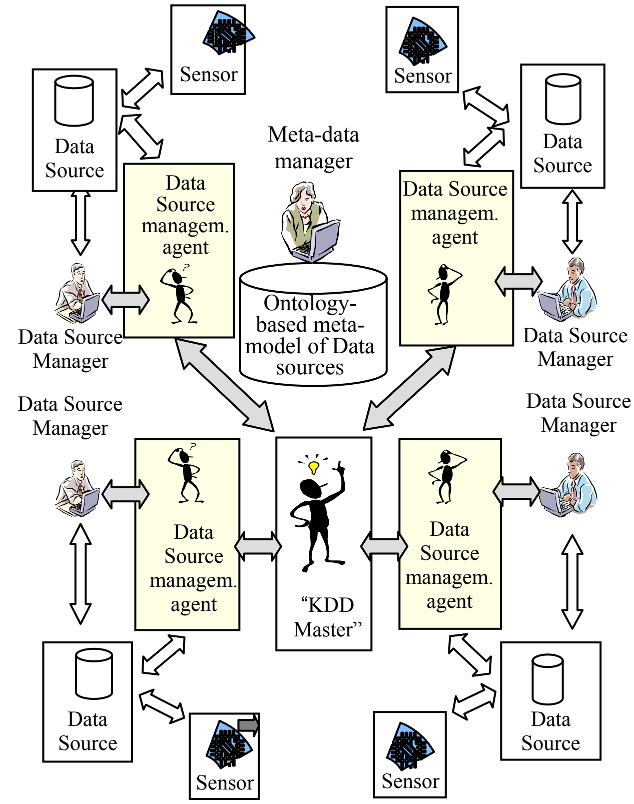

Figure 6. Distributed design of distributed ontology

shared thesaurus providing for *monosemantic understanding of the terminology* used in formal specification of domain entities. This problem arises due to the fact that specifications of data belonging to particular sources are being developed by different experts and in most cases these processes are independent (see Figure 6). The experts can denote different domain entities by the same name and vice versa, they can denote the same entity differently that can lead to misunderstanding.

Next class of problems solved via use of ontology called *non-coherency of data measurement scales* comes out of the fact that the same entities can be represented in different sources by various data structures but in IF procedures all of them have to be used equally. That is why it is necessary to provide distributed data *for consistent representation.*

The third problem is so-called "*entity instance identification problem*" [6]. The data specifying an object is represented in several information sources. Therefore each information source only partially specifies it. Object complete specification is made up of data fragments distributed over the information sources and to form a complete object specification, a mechanism to identify such fragments is needed. It should be noticed that some fragments of information associated with an object can be absent in a number of sources.

The protocol of distributed design of distributed ontology is now developed in detail and implemented as a component of software tool supporting IF system design and implementation (see Figure 4). The user-guided process of ontology design is also to be supported by use of a particular editor for ontology specification. The editors of such kind are being developed in Semantic Web community [22]. As a rule, the ontology is specified in a standard language like XML, RDF, DAML+OIL that are also being developed in Semantic Web scope. In our software tool the XML language is so far used.

5 Meta-models of Information Fusion

Although to date several strategies for data and information fusion are proposed [10], the most popular and advantageous one is the strategy using a multi-level hierarchy of classifiers. In it, the source-based classifiers make decisions on the basis of information of particular sources followed by meta-level decision making based on combining of the source-level decisions. The advantages of such a scheme are (1) decrease of information exchange; (2) simplicity of decision fusion of source-based classifier even if they use data and information of different structure, certainty, accuracy, etc.; (3) possibility to use mathematically sound mechanisms for combining decisions of multiple classifiers. In large scale applications this strategy is more accurate and computationally efficient. Moreover, in some applications this strategy is the only applicable, e.g., if the data and information of different sources is private and the holders do not want to share it but agree to share decisions produced on the basis of private data and information.

Different variants of structures according to whose decisions of particular classifiers may be fused exist. In accepted multi-level decision fusion, lower level classifiers (*base-level* classifiers) produce decisions on the basis of data and information of particular sources. At the higher level these decisions are combined by *meta-classifier* according to a strategy. The structure of decision combining is called here *meta-model of decision fusion*.

The choice of a meta-model of decision fusion influences on the architecture of IF system components, on components aiming at support for training and testing of classifiers and on interaction of agents of IF software tool. In some cases, decisions of base-level classifiers are sent to meta-level that combines these decisions. In other cases decision combining is used even at source level. In this cases the results of source-based decision combining are forwarded to meta-level. Finally, one can use the meta-model of decision .fusion, in which both meta-level and part of base-level decisions are forwarded at the higher level, at which they are combined together with the decisions produced by classifiers of other sources.

Design of information fusion meta-model is a functionality supported by IF software tool under consideration. The protocol A1 (Figure 5) supports this design. This protocol is developed in detail and implemented but we omit its detailed specification due to lack of paper space and to reserve a space for a more detailed specification of the core protocol of the technology that is Distributed Data Mining (DDM) protocol.

6 Distributed Data Mining

To make explanation of the DDM protocol (Protocol A3) more clear, it is reasonable to firstly describe algorithms used for decision combining.

6.1 Combining of decisions of multiple classifiers

It was above noted that in this research and development we follow the strategy of info0rmation fusion in which IF is considered as hierarchy of multiple classifiers producing decisions on the basis of particular data sources followed by combing these decisions at the meta- level. In the most IF tasks "*decision*" is understood as *classification* of an entity (object, state of an object, etc.), i.e. assigning the entity a class label from a fixed set.

To date several approaches to decisions combining are developed. They can be grouped as follows:

1. *Voting* algorithms;
2. *Probability*-based or fuzzy algorithms;
3. Meta-learning algorithms using an idea called *stacked generalization*;
4. Meta-learning algorithms based on *classifiers' competence evaluation*.

Voting methods were developed about twenty years ago and were historically the first [14]. Due to their simplicity and satisfactory accuracy in many applications these methods are to date in use. The most simple of them is called "*majority voting*" [4]. The "*weighted voting*" approach ([3], [4], etc.), which is a little more sophisticated, was implemented in many particular forms and is currently in broad use.

The methods of the second group are based on probabilistic models like Bayesian model of a posteriori probability assessment, Bayesian networks, Dempster–Shafer theory of evidence, and also on fuzzy set-based models (see [2]). These models are in some sense

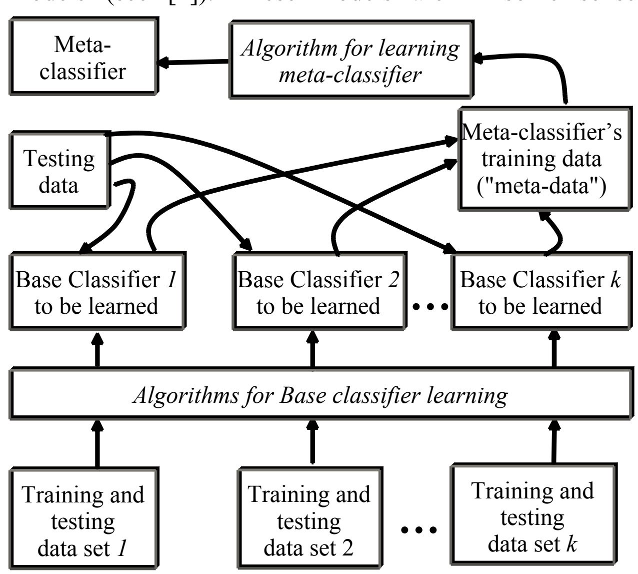

Figure 7. Meta-classification scheme

"classical", they have long history and do not need any comments or references. To our opinion probabilistic and similar models are applicable if the dimensionality of the classification task is small and there is enough information for empirical assessment of needed probabilistic characteristics with satisfactory accuracy and reliability. In IF scope such methods can reasonably be used at higher levels of decision combining.

However, at present the Knowledge Discovery from Databases (KDD) R&D community pays the most attention to the methods of combining decisions that use some knowledge about properties of base-level classifiers. General idea of this group of approaches that was proposed in [19] is called "*stacked generalization*". Although the idea of *stacked generalization* itself is very simple, it turned out very effective and gave birth to several particular methods of decision combining. The most promising variations of *stacked generalization* are proposed in [17], [13] ("*meta-classification*"), [5]

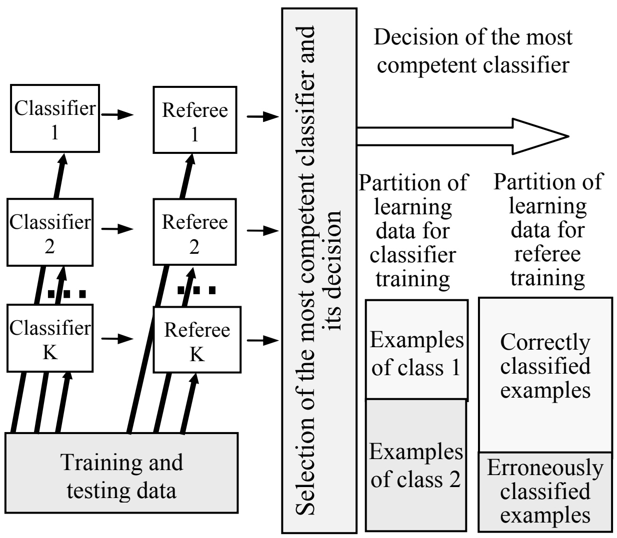

Figure 8. Explanation of the idea of competence-based approach to combining decisions of multiple classifiers

("*cascade generalization*"), and in some others.

Generalized structure of decision combining based of *stacked generalization* (for its "*meta-classification*" variant) is explained in Figure 7. The experience proved that base classifiers, which decisions are supposed to be combined, are to be "diverse", i.e. they must be at least either based on different learning algorithms or to be learned on the basis of different training and testing data.

In general, *stacked generalization*-based methods of decisions combining are popular and still being actively researched.

The fourth group of methods is based on the *evaluations of classifiers' competences* with regard to each particular record of input data, specifying an object. The main idea of competence-based methods of decision combining is to assign to each particular classifier the region in attribute space where it is most competent as compared with the other base-level classifiers. Firstly this idea was proposed in the papers [16] and [11]. The core of this idea is that a special procedure called "*referee*" (see Figure 8) is associated with each particular classifier. A responsibility of referee is to assess the competence of the respective classifier with regard to the particular input data [12]. To be able to solve this task, the referee has to be trained. Referee training is reduced to the routine learning task, which can be solved on the basis of the same training and testing data that are used for training and testing of classifiers themselves. A specific of the last task is that in it other partition of training data is used. For referee training, the same training and testing data are partitioned into two subsets of positive and negative examples like shown in Figure 8.

In competence-based methods, decision combining consists of two steps: (1) detection of the most competent classifier and (2) selection of the classification produced by the most competent one.

Further important development of this method was proposed in the paper [18], at that the last paper proposed the definitely significant improvement of the basic method. In general, competence-based methods are very promising ([11], [12], [18]). Their advantages are better accuracy (as compared with the voting and stacked generalization-based methods) and its capability to preserve already existing set of classifies unchanged if a new classifier is inserted in classification system.

Two types of methods discussed in this section, i.e. meta-classification and competence-based methods are included into the multi-agent IF software tool as decision combining methods in the server (library) of KDD algorithms.

6.2. Distributed Data Mining Protocol

This protocol is the core of IF system technology because it conducts training and testing of particular classifiers and also manages decision combining that are the basic IF system functionalities. IDEFO diagram of this protocol is presented in Figure 9.

It involves in interaction all agents supposed by IF software tool architecture that are KDD master, Meta-level KDD agent, Agent-classifier of meta-level and Information Fusion management agent situated on the Host of meta-learning server, and also Data source management agents, KDD agents of base classifiers and Classification agents of data and information sources. The basic processes realized by the above agents in this protocol correspond to the developed technology of IF system training at the stage following Distributed application ontology design and Design of meta-model of decision making by IF system.

The main processes of this protocol are as follows:

1. Selection of data for training and testing of Base Classifiers (A2.1).
2. Classifier's training and testing (A2.2).
3. Meta-classifier training management (A2.3).
4. Computation of data for training and testing Meta-classifier (A2.4).
5. Meta-classifier's training and testing (A2.5).

6. Preparation of the IF system for use in decision making mode (A2.6).

The sub-processes (sub-protocols) of the DDM

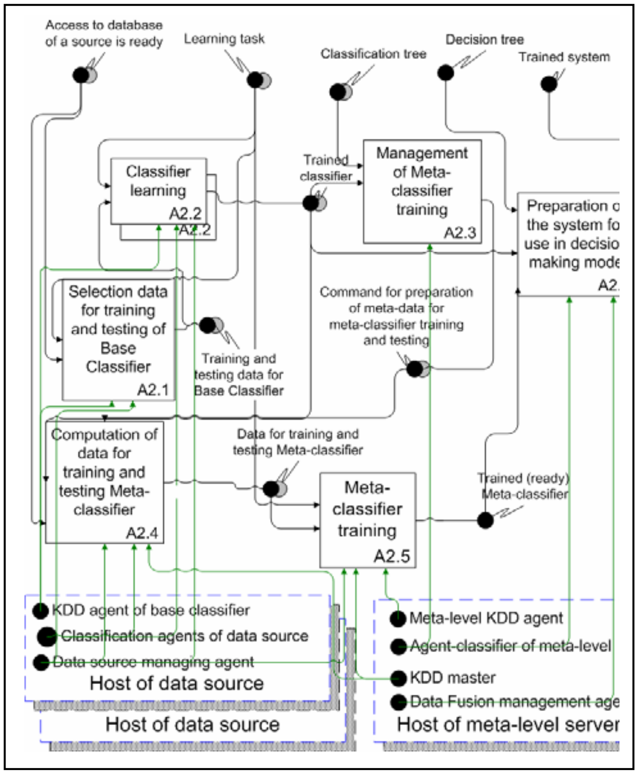

Figure 9. Distributed Data Mining protocol used for training and testing of IF system classifiers

comprising A2 protocol are specified at several levels of details up to the sub-processes that don't suppose distributed execution. This protocol is now about implemented.

The set of techniques used for learning of base-level classifiers, meta-classifier and referees and included into the library of training and testing methods comprises VAM algorithm (Visual Analytical Mining, [8]) for mining numerical data, GK2 algorithm [14] for extraction rules from discrete data and also Frequent Pattern grows algorithm [10] for mining association rules.

7 Case Studies

Two case studies were used in design and validation of IF MAS software tool prototype. They were developed with use of Multi-Agent System Development Kit [7] developed by authors of this paper. The prototypes implemented case studies outlined below.

KDDCup-99 –based Case study of IF system

Application corresponding to KDDCup-99 dataset [20] deals with Intrusion Detection Learning Task. Inherently this data are not distributed but it was split artificially to model multiple sources and use the result as a case study. The KDDCup-99 dataset is specified by 36 attributes of various types (numerical–28, categorical–4, Boolean–4), and the total size of data records *used in case study* (but not in dataset) is equal to 33460, at that *TT*=7100 of them were used for training and testing of base classifiers and meta-classifier and the rest, *FT*=26360, were used for evaluation of the accuracy of the developed IF multi-agent system. The *TT* data set was artificially split into two data sources, DS1 and DS2 (they share 1Boolean attribute). In turn, DS1 and DS2 data sets were also split into 3 and 4 subsets respectively. The last splitting aimed to form training and testing data for particular base classifiers and meta-classifier at that the total number of base classifiers was chosen equal to 7 (3 of them were used in DS1 and 4–in DS2). The scheme of interaction of base classifiers and meta classifier is given in Figure 10. The base classifiers differ in attribute sets and also in training and testing data sets and some of them also differ in learning algorithms used. Two basic algorithms of learning were used in the case study: *Visual analytical Mining* [8], dealing with numerical data, and *GK2* [9] dealing with discrete data. Both algorithms were developed by the paper authors.

This case study was used for evaluation of correctness, advantages and drawbacks of the partially developed IF MAS software tool, of the multi-agent approach to the design and implementation of IF systems and also to validate its feasibility and applicability in practice.

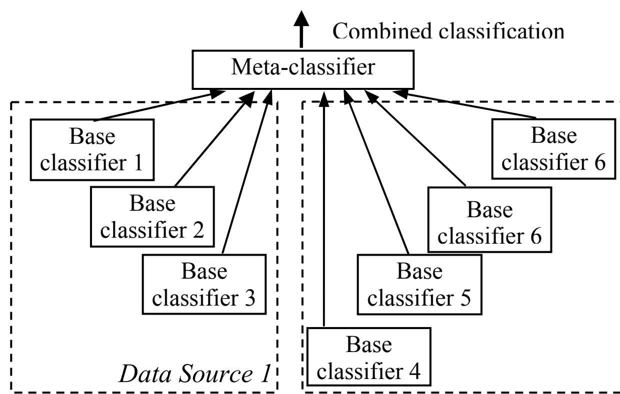

Figure 10. Classification structure in KDDCup case study

Multi-Spectral Image classification

The second case study which objective is multi-spectral image classification has also been used for validation of the developed software tool. It uses Landsat Scanner image dataset of UCI repository [21].

8 Conclusion

The paper presents the developed multi-agent technology and software tool for IF systems design and implementation. IF system design technology puts several new non-specific tasks and challenges. Some of them are in the focus of the paper. At that, the key ones come out of the fact that information sources are distributed, heterogeneous and, as a rule, are of large scale. This data and information sources are spatially distributed or, at least, they are represented in different databases and/or located on different hosts. Heterogeneity is entailed by the diversity of possible data and information representation structures, differences in used specification languages, diversity of information natures (geographical, statistical, etc.), etc. These and some other specific properties of data and information to be processed in IF applications constitute basic challenges considered in the paper. Within them, four issues are of the most significance. The *first* issue concerns the IF system architecture which in this development is considered as multi-agent system. The *second* one concerns decisions combining produced on the basis of particular sources that requires the design of a meta-model decision fusion. The *third* issue is distributed design of IF system ontology. Finally, the *fourth* issue that is the most challenging one is DDM. The main results of the paper concern analysis of these issues, proposed solutions of the associated tasks and development of the feasible technology and supporting software tool. Although the main paper subject is IF technology and software tool, its results provide also the basis for Multi-agent Distributed Data Mining technology of general purpose.

Future research will be focused on the implementation issues of IF software tool, and its use for the design of particular IF applications to accumulate experience and to make the IF software tool more industrial–oriented.

Acknowledgement

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