



Certainty, trust and evidence: Towards an integrative model of confidence in multi-agent systems



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ABSTRACT

Introducing confidence in multi-agent systems gives agents a form of control in making decisions and helps to improve the decision making process in such systems. Consequently, modeling confidence of agents is important in heterogeneous agent communities. The inability to detect an agent's confidence can be a reason for inaccurate decision. Several weaknesses have been found in current trust and confidence models in multi-agent systems. Current models propose that the trust of an agent depends on its reputation, past experience, and observations on its behavior. This paper presents another approach to agent-based confidence modeling. Initially, it integrates two confidence requirements, namely, trust and certainty. To further strengthen the model, we include evidence as an additional requirement to the model by which trust and certainty of an agent can be verified. This paper establishes bisection between trust, certainty, and evidence spaces. The modeling mechanism eliminates untrusted opinions, since such certainty level might not be valuable in all states. The proposed technique also separates the global confidence scheme from the local confidence scheme, so as to provide greater reliability for confidence detection.

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1. Introduction

Cooperation among agents is very important in achieving the goals of a multi-agent system (MAS), but sustaining cooperation in uncertain environments is risky. For example, agent A might believe agent B, who is actually giving inaccurate information (Barber, Fullam, & Kim, 2003). Agent-based systems have specific peculiarities that require users to support their mechanisms. For instance, the basis of such systems on decision-making indicates that decisions are based on agents' beliefs or specific plans. Beliefs obtained from agents must have reasonable confidence level to be useful. Furthermore, collecting information from multiple sources may depend on services not under the particularity of the agents. Such situation calls for a reliable confidence model of services and information provided by other third-party systems. We propose evidence as an additional requirement to the model by which trust and certainty of an agent can be verified. However, to include evidence as another component for a confidence model, we need to

know that information was collected in a reliable way, i.e., with certainty, trustworthiness, etc.

In MAS, measuring confidence is important because confidence gives a form of control in an environment. Collecting the opinions of agents, especially those agents whose trust and certainty are unknown, is risky in making a final decision. The confidence of agents cannot always be judged at face value as the factors by which they are detected are important. For example, the trust of an agent, the reputation with which an agent was evaluated based on past history, collected evidence, and the certainty affect the confidence of agents. In systems of homogenous multi-agents and independent internal structures, the ability to detect the confidence of an agent needs a rational algorithm. Ensuring the ability to check confidence factors is an important step in ensuring that opinions of agents are credible.

In this paper, we propose a new definition of confidence and we show how the factors of confidence can be detected. While other factors may be appropriate for detecting confidence value, we use evidence to detect the confidence level of agents. We aim at improving the efficiency of trust and certainty mechanisms by endowing an Evaluation Agent (EA) with some extra information to detect the confidence of agents. In our model, the requirements can be explained as follows: Firstly, the model must support the

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confidence metric of an agent, which utilizes trust and certainty. Such model allows one to distinguish between agents in that one agent can be recognized as more confident than others. Higher confidence level means a greater influence on the process of decision-making, while a lower confidence level means otherwise. Secondly, the evaluation agent must not assume that the opinions of other agents are enough for reaching a decision. Thus, the model must be able to collect evidences from the environment to support the opinions of agents. However, current models do not allow an agent to assess the certainty level of agents' opinions and to use the result for accurate evaluation of the opinions provided by those agents. To achieve this requirement, we have developed a model named Agent Opinion Confidence (*AgentOpCo*), which is a confidence model that detects the confidence of agents in multi-agent systems.

This paper is organized as follows: Section 2 reviews the related work in the context of this study. Section 3 describes the proposed confidence model. Section 4 builds up the mathematical model of confidence. Section 5 presents the basic *AgentOpCo* model with an example to demonstrate the model and evaluate its effectiveness. Section 6 concludes the paper.

2. Related work

2.1. Trust

Trust is the subjective probability by which an individual, A, expects that another individual, B, performs a given action on which its welfare depends (Touhid, Josang, & Xu, 2010).

The literature is rich with different approaches to trust detection in MAS. The term "trust" is used in building MAS that may encounter uncertain, incomplete, or incorrect information that had been collected from several sources (Barber et al., 2003). "An agent's trust in another can be understood as a belief that the latter's behavior will support the agent's plan. For rational agents, trust in a party should be based substantially on evidence consisting of positive and negative experiences with it" (Wang & Singh, 2007). Yu and Singh (2002) finds an inverse relationship between conflict and trust.

The degree of trust increases as the amount of information increases and the degree of trust decreases as the amount of information that conflicts with past experience increases. Huynh, Jennings, and Shadbolt (2006a) includes heuristics that merge several information sources for detecting trust. Alfarez and Hailes (2000) models the trust and reputation of agents in an interaction environment (TRAVOS). The study calculates trust depending on past interactions between agents. If there are no available experiences from agents, the model gathers reputation information from third parties. Collecting agent opinions is soliciting the reputation of an agent, which ensures its trustworthiness if they have no personal experiences based on it. They assess the confidence of the agent on the level of trust compared with another agent (certainty of trust). Teacy, Patel, Jennings, and Luck (2005) proposes a model to measure a probability of trust by modeling trust in terms of confidence such that the expected value of trust appears within an indicated error tolerance. In their model, the confidence of an agent increases with the error tolerance. Wang, Mellon, and Singh (2010) uses a reputation system for finding trust estimation, and classifies reputation systems into two types, namely, centralized and distributed.

Fullam, Muller, Sabater, Topol, Barber, Rosenschein, and Vercauter (2005) build a test bed system to test the opinions of several researchers. Each researcher has a separate agent that represents his/her strategy for solving a specific game problem. An evaluator agent then gathers the opinions of researchers to

select the best opinion depending on two developed models, which are competition and experimentation. The system proposes methods depending on the social welfare, which allows researchers to define several metrics. Huynh, Jennings, and Shadbolt (2006b), Ramchurn, Sierra, Godo, and Jennings (2003), and Sabater and Sierra (2001) build their trust model by using agent confidence and reputation. An agent's reputation depends on past experience, and in case there is no past experience about an agent, their model asks other agents. Hence, measuring agent confidence depends on the experience of other agents about the specific agent.

2.2. Certainty

Certainty "is a measure of the confidence that an agent may place in the trust information", they are mentioned that measuring a certainty can filter out insufficient information even with high trust degree (Bilgin et al., 2012).

It is defined as a mathematical value that is equal to the probability of right and complete information. One of the important features of information is its indistinctness, which Imam (2010) termed as "uncertainty". Berenji (1988) defines uncertainty as a lack of complete information, or randomness. Douglas (2010, chap. 4, 5, & 6) defines uncertainty as "the lack of certainty, a state of having limited knowledge where it is impossible to exactly describe existing state or future outcome, more than one possible outcome." Information can be certain or uncertain, may come in different degrees, and different degrees of certainty affect the beliefs of an agent (Paggi & Amo, 2010). Wang et al. (2010) defines certainty as "a measure of the confidence that an agent may place in the trust information." The study mentions that measuring certainty can filter out insufficient information even with a high degree of trust. Paggi and Amo (2010) discusses the concepts of uncertainty, and shows the relation between uncertainty and the effects on system design. Wu, Su, Luo, Yang, and Chen (2009) extends the concepts of knowledge, belief, and certainty for MAS. The study introduces a merging of the logic of knowledge, belief, and certainty in MAS. They present a dynamic logic of knowledge, belief, and certainty for MAS (CDKBC logic). Halpern (1991) uses the relation between knowledge and certainty to build his model. He defines fact and certainty as "known if it is true at all worlds an agent considers possible, and is certain if it holds with probability 1."

Wang et al. (2010) uses certainty to describe the degree of trust of each agent for another agent in the system. He proposes a concept of trust in which "an agent Alice's trust in an agent Bob in terms of Alice's certainty in her belief that Bob is trustworthy." We, however, propose a different meaning, which is "an agent Alice's trust in an agent Bob, but Alice is not sure about the certainty of Bob." Thus, Bob is considered a trustworthy source, but we nonetheless need to check the certainty of his information. An example for the difference between certainty and trust, assume that Alice asked Bob about a specific event, Alice trusts Bob. Bob is trustworthy, but he may nonetheless give an uncertain answer due to his uncertainty.

2.3. Evidence

One of the key challenges for the MAS is determining trust based on information from different sources that have different degrees of trust. Wang et al. (2010) defines evidence as "conceptualized in terms of the numbers of positive and negative experiences." When an agent makes unambiguous direct observations of another agent, the corresponding evidence could be expressed as natural numbers (including zero). Wang and Singh (2007) argues that trust should be dependent on evidence. They offer a theoretical model of trust development such that a trust depends

on evidence. Their model explains a new direction of a mathematical understanding of trust. Their motivation is to merge evidence in the context of trust.

Teacy, Patel, Jennings, and Luck (2006) asserts that certain environments make it suitable for a truster to boost the information from the opinions of a third party. An example about the relation between evidence and certainty of trustworthiness is, “Alice deals with Bob four times or obtains (fully trustworthy) reports about Bob from four witnesses. In either case, her evidence would be between 0 and 4 positive experiences. It seems uncontroversial that Alice’s certainty is greatest when the evidence is all in favor or all against and least when the evidence is equally split.” Yu and Singh (2002) divide the evidence into three types, namely, negative, positive, and neutral. They assume that experiences produce a state of uncertainty.

Yukalov and Sornette (2012) argue that additional information collected through interactions with the society reduces errors in decision making. However, if there is a conflict between positive or negative evidence, there is no effect on uncertainty. Their model discovers untrue recommendations by detecting unsuccessful recommenders, then decreasing the weights assigned to them.

2.4. Confidence

We defined confidence as a combined model that considers social trust and certainty concepts, supported by collecting evidences. Heras, Navarro, Botti, and Julián (2010) define confidence as a value that represents the confidence that an individual agent has in some argument. Confidence detection depends on trust in the opinions of an agent or a certainty of these opinions. However, in a MAS environment, such agents may hide or lie about some actions. By designing a testing system for the confidence of agents, we avoid deception from an agent. Miles, Groth, Munroe, Luck, and Moreau (2007) argues that designing an agent-oriented model must lessen inaccuracy and to present confidence to make users know how the results of MAS come about.

2.5. Trust and confidence

Reagle Jr. (1996) classifies trust into three types. First, “trust as truth and belief” represents trust on behavior or quality of an entity. Second, “trust as expectation” expects an assertion to be true. Third, “trust as commerce” is the confidence in buyer ability and the intention to pay in the future. We adopt the first class and define trust as one of the factors of confidence. Earle and Siegrist (2006) addresses the relationship between trust and confidence by developing a conceptual framework that explains the distinction between both concepts, and integrates them in a trust, confidence and cooperation (TCC) framework. The study asserts that social trust dominates confidence, and assumes that confidence builds on preexisting relations of trust. “It is assumed that where social trust is present, some performance failings might lower confidence a little but would not undermine a willingness to cooperate. By implication, when social trust is absent or low, performance failures should lead to a swift response from consumers, such as complaints or a lack of cooperation.”

Huynh et al. (2006a,b), Maximilien and Singh (2004), and Sen and Sajja (2002) build their trust model by using agent confidence and agent reputation. Agent reputation depends on past experience. In a state where there is no past experience about an agent, their model consults other agents. Measuring the confidence of a particular agent depends on the experiences of other agents regarding the specific agent. From a social science perspective, Wood (2012) defines different aspects of trust and confidence. Confidence “is something we may have in institutions and their behavior,” whereas trust “generally refers to people.” If we

assume that MAS is an institution and an agent is a person, then we need trust for each agent to assert MAS confidence. The current approach to trust has many default points, which are as follows.

2.6. Dependency between confidence and trust

Confidence does not have a single definition. For example, Oxford dictionary defines confidence as “the state of feeling certain about the truth of something or someone,” which emphasizes confidence both as a certainty and a truth about someone or something. However, the definition of trust in the Oxford dictionary also includes, “reliance on some quality or attribute of a person or thing, or the truth of a statement.” Some languages do not differentiate between the two concepts, and the literature includes several definitions, which can lead to confusion (Fife-Schaw, Barnett, Chenoweth, Morrison, & Lundéhn, 2008). There are several research on the relationships between trust and confidence (Earle and Siegrist (2006), Fife-Schaw et al., (2008), Siegrist, Earle, and Gutscher (2003), Vickerstaff, Macvarish, Taylor-Gooby, Loretto, & Harrison (2012)). Fife-Schaw et al. (2008) distinguishes between confidence and trust in that confidence is based on past competence, whereas trust is based on having similarity value in mind. In the case of having insufficient past experience to estimate confidence, social trust will become important, and can be used as an attribute for an interested party. Earle and Siegrist (2006) distinguishes between trust and confidence by proposing two types of trust. Generalized trust is a kind of attribute, whereas trust in certain factors is towards a specific agent. Confidence is an expected belief based on experience. Current approaches address trust as an extensive concept and consider confidence as one of its detecting factors.

2.7. Evidence dependency

Current approaches that consider evidence as an important factor for detecting trust detect evidence based on past experience with agents or the reputation of an agent. Wang et al. (2010) build a system that detects evidence depending on past experience with an agent, but Sen and Sajja (2002) build a system that detects evidence depending on the reputation of the agent.

3. The proposed confidence model

Our approach models confidence based on three sources of information, which are the degree of certainty regarding the opinion of each agent, agent’s trust, and evidence for both certainty and trust. We combine trust and certainty values into a single composite measure to integrate a holistic view of the confidence of an agent. The concept of confidence is broken down into several factors, which may be integrated to produce the final confidence evaluation (degree of confidence).

One of the main specifications of our design is our assumption that there is an Evaluation Agent (EA) that seeks the opinions of other agents to make its decision. Thus, the EA have more confidence in some agents than others, which could change based on evidence. In order to process these evidences, we introduce an Evidential Agent (EVA). Here, we include evidence as an additional factor that sets the confidence values of agents. Assuming positive evidence for opinions matching agent I’s certainty and trust, then it can be said that confidence increases as I’s opinion matches the belief of the EA.

3.1. Basic concept

The basic step of a computational confidence model is that it should provide a metric for calculating the certainty and trust of all agents in a system. We consider three concepts in a multi-agent system; trust, confidence and evidence.

Most systems that we reviewed only consider either trust or certainty as a separate model in a multi-agent system. These systems do not exploit the certainty of trust as an integrated model. To overcome this deficiency and provide a near-perfect model of confidence, existing trust and certainty models need to be extended. A strategy that detects trust needs to be conceived and the certainty of agents needs to be analyzed to develop the confidence model.

We emphasize that these three concepts are integrated as shown in Fig. 1. For example, in an evidential trust area, there is a trustable agent and an evidence for this trust, but there is no certainty, here, we do not ensure that this trustable agent is certain about its belief. In an evidential certainty area, there is a certain opinion with evidence, but what is the benefit of certainty without trust? In the third area, that contains trust with certainty, we need some evidence to assess these two factors. Truly, a complete confidence area integrates these three factors.

We propose a new concept that defines two types of confidence, namely, Local Confidence (LC), and Global Confidence (GC). Consequently, we assume the existence of local and global trust and certainty.

Depending on local and global trust and certainty considerations, new confidence detection is made each time an interaction occurs between agents. The detection depends on satisfying factors that are based on an analysis of the agents' behavior. We explain how the confidence calculating strategy is implemented, how each agent provides local certainty and trust, and how an Evidential Agent (EVA) observes an agent's actions to assess the global confidence of the agents.

3.2. System architecture

Our confidence model is described as follows: First, we have a decision to be made based on collected agents' opinions. We need to determine the confidence value for each agent to resolve any opinions' conflicts. We have two agents:

- Evidential Agent (EVA): Collects evidences from the environment.
- Evaluation Agent (EA): Responsible for calculating confidence value for agents.

The EA uses two steps to assess the total confidence of other agents. First, GC is the evaluation that the EVA agent makes based

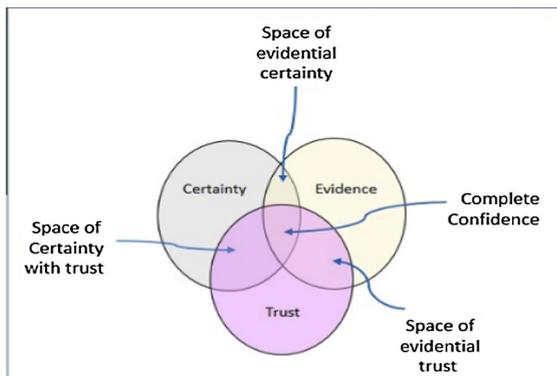


Fig. 1. Integrated confidence model.

on the result of the collected evidence of trust and certainty from the environment. Second, LC is the evaluation of the EA agent itself that assesses the local confidence based on the certainty value of the other agents' opinions (provided by the agents themselves). Fig. 2 shows an illustration of this concept that depicts agents' trust and certainty.

The total confidence is defined in Eq. (1).

$$\text{Total Conf} = LC + GC \tag{1}$$

To define confidence, we consider an agent to be certain if it has a high assertion, and we consider it to be trustworthy if it has high performance particularly in the trustworthiness criteria. Certainty can be measured from two sources, namely, the agents (each agent give its opinion and it is certainty about it) and the certainty evidences (see Fig. 3).

We understand confidence based on the probability of outcomes and adopt an idea of a confidence space consisting of certainty, uncertainty, trust, and untrustworthiness. Thus, we distinguish among four situations:

- High trust and high certainty.
- High trust and low certainty.
- Low trust and high certainty.
- Low trust and low certainty.

3.3. Notational definitions

We define the following notation that are be considered important for our model:

- A set of agents, $A = \{a_1, \dots, a_n\}$, where each a_i represents an individual agent.
- Trust: Given two agents $a_i, a_j \in A$, the trust value of a_i on a_j is represented as a variable $T_{ai,aj} = [0 \dots 1]$. Here, $T_{ai,aj}$ specifies the probability that a_i trusts a_j . For example, if $T_{ai,aj} = 0.5$, then a_i trusts a_j half of the time, while if $T_{ai,aj} = 1$ then a_i has complete trust in a_j .
- Certainty: The value of a_i 's certainty is represented as a variable $Cer_{ai} = [0 \dots 1]$. Cer_{ai} specifies the agent's certainty about its opinion.
- Importance of trust to a system is represented as I .
- A set of opinions, O , is collected from agents about some event by an Evaluation Agent (EV). Each opinion is represented by a tuple, $O_{ai} = (a_i, T_{ai}, Cer_{ai})$.
- A set of evidences, E , is collected by the Evidential Agent (EVA), and represented as a tuple, $E = (PE, NE)$, where PE is the number of positive evidences, and NE is the value of negative evidences.

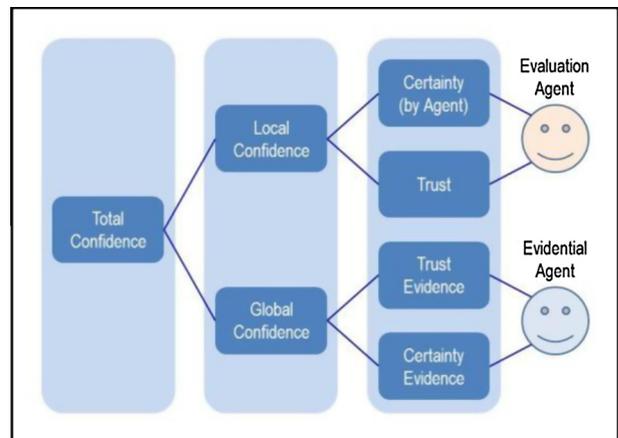


Fig. 2. The concept of integrated confidence model.

4.2. Global confidence

In open environments, in which agents contact with each other, computational models of certainty and trust have an important role to play in determining global confidence values of agents.

4.2.1. Modeling global trust

Teacy et al. (2005), Bilgin et al. (2012), Heras et al. (2010), uses reputation as a basic factor to detect the trust of an agent. We calculate the value of reputation based on the connection density between agents. First, we define the connections between agents and the degree of these connections. In the set of all agents, $A = \{a_1, a_2, \dots, a_n\}$, we assume that these agents interact with each other and that the agents may have different degrees of connections between them. We denote a reputation of a_1 based on a_2 's opinion as R_{a_1, a_2} . The weight, W ($W > 1$), of each reputation is denoted as WR_{a_1, a_2} . Here, WR_{a_1, a_2} is evaluated from the following equation:

$$WR_{a_1, a_2} = CN_{a_1, a_2} * O_{a_2} \quad (6)$$

where CN_{a_1, a_2} is the number of connections between a_1 and a_2 and O_{a_2} is agent a_2 's opinion. If we assume three connected agents a_1 , a_2 , and a_3 , to calculate the trust value of a_1 , we use a_1 's reputation based on agents a_2 's and a_3 's opinions. Here, CN specifies the weight of each opinion.

$$T_{a_1, a_2} = WR_{a_1, a_2} = CN_{a_1, a_2} * O_{a_2}$$

$$T_{a_1, a_3} = WR_{a_1, a_3} = CN_{a_1, a_3} * O_{a_3}$$

where T_{a_1, a_2} denotes the trust of an agent a_1 based on a_2 's opinion.

4.2.2. Modeling global certainty

The EA detects the certainty of an agent based on the predefined factors of certainty. Assume we have M certainty's factors, $CF = \{\phi_1, \phi_2, \dots, \phi_M\}$ and that an agent, a , satisfies different values for each factor. Eq. (7) calculates the certainty of an agent based on the different rates of certainty.

$$\text{CERTAINTY} = \sum_{i=1}^{i=M} \left(\frac{\text{Satisfied Factor}}{\text{Total Factors}} \right)_i \quad (7)$$

where Satisfied Factor/Total Factors denotes the certainty factor ϕ .

4.3. Modeling evidence

Wang et al. (2010) explains the idea of evidence by thinking of an agent's (rating) experience on a (rated) agent as a binary event: positive or negative. "Evidence is conceptualized in terms of the number of positive and negative experiences. When an agent makes unambiguous direct observations of another, the corresponding evidence could be expressed as natural numbers" (Wang et al., 2010).

We calculate the value of PE (positive evidence) and NE (negative evidence) for trust and certainty based on the environment outcomes observed by the EVA . First, we define initial values for the two variables of PE and NE that represent the beliefs of EVA about the evidence from the environment. We assume, prior to observing any event in the environment, that EVA believes that the evidence is equally valid, i.e. the initial settings of PE and NE for EVA are $PE = NE = 0$. From observations of the environment, we add the number of positive evidence to the initial setting of PE , and the number of negative evidence to NE .

5. AgentOpCo model

AgentOpCo provides the EA with two methods for assessing the trustworthiness and certainty of another agent. First, the EA makes

the assessment based on trust and certainty values of agents. Second, the EA may assess the trust and certainty based on the external evidence from the EVA.

5.1. Calculating confidence value

Assume that a situation exists that requires the opinions of agents. The calculation of the confidence value follows the following procedure:

1. EA collects opinions from agents (let say O_1 and O_2).
2. EA evaluates the local confidence: EA has, in its common knowledge, the trust value for each agent after collecting the agents' opinions.
3. Each agent gives its certainty value of its opinion.
4. EA adds the collected information into its common knowledge as follows:

Agent 1 ($D1$):

Trust-value (T_1).
Certainty-value (Cer_1).
Opinion (O_1).

Agent 2 ($D2$):

Trust-value (T_2).
Certainty-value (Cer_2).
Opinion (O_2).

5. Calculate the Local Confidence (LC).

EA gets the evidence from the Evidential Agent (EVA): The Evidential Agents (EVA) observes the environment, if it has collected trust and certainty evidences, it confirms EA as follows:

CONFIRM. Agent 1 ($D1$): Trust-Evidence (TO_1).

Certainty-Evidence ($CerO_1$).

CONFIRM. Agent 2 ($D2$): Trust-Evidence (TO_2).

Certainty-Evidence ($CerO_2$).

If EVA cannot find an evidence, it sends NOEVIDENCE to EA.

6. EA calculates the Global Confidence (GC).

7. Calculate the Total Confidence.

After this procedure, the EV sends one of two operators to $D1$ and $D2$ that includes:

ACCEPT (A_1) Approve the a_n opinion.

REJECT (A_2) Reject the a_n opinion.

5.2. An example scenario for using the proposed model

To explain the proposed model, we assume a group of agents, in which a process of opinion gathering takes place. The group of agents may be a small one, and these agents neither share nor disregard the opinions of other agents. The EA gathers the opinions of all agents in forming a final decision. The decision can be reached by different confidence values, which the EA derived from the opinions of all the agents.

Our environment consists of a two diagnosis agents, $D1$ and $D2$ and a patient agent, P . An EA ultimately obtains a confidence value for all diagnosis agents based on the values of GC and LC . For our purpose, the roles of $D1$ and $D2$ are to diagnose the state of the patient agent, P . The LC is calculated based on the trust and certainty values gathered from $D1$ and $D2$, while the GC is calculated based on the collected evidence of trust and certainty about $D1$ and $D2$. Here, local confidence sources are divided into two types, which are satisfied trust factors and opinion certainty.

5.2.1. Calculating the local confidence

Trust factors differ depending on the state. In the current scenario, we assume that the trust factors are the following:

- Years of service (max. of 30 years, min. of 1 year). If a diagnosis agent has 10 years of service, the value for this factor is calculated as: $10/30 = 1/3$.

- Scientific degree (PhD, Master) (2 for PhD and 1 for Master). If the diagnosis agent has a PhD, then the value for this factor is calculated as: $2/2 = 1$.
- Past rate of wrong diagnoses, based on the profile of a doctor. We calculate the rate of wrong diagnoses made in the past. For the diagnosis agent, if the total number of diagnoses made is 50, and has 10 wrong diagnoses, the value for wrong diagnosis factor = $10/50 = 1/5$, but this value must be negative ($-1/5$) due to its negative implication.

The following table contains the opinions (diagnosis) and certainty of the agents with satisfying trust factors. We show the calculation of local confidence based on the values shown in Table 1 below.

We assume the trust factors for this state as follows:

- Years of services >10 years.
- Scientific degree is PhD.
- Wrong diagnosis rate <30%.

By using Eq. (3), the evaluation agent will calculate the trust value for D1 and D2:

$$E[T|SF, USF] = \frac{SF}{SF + USF}$$

where T : trust; SF : satisfied factors; USF : unsatisfied factors.

$$E[T_{EA,D1}|SF, USF] = \frac{3}{3} = 1$$

$$E[T_{EA,D2}|SF, USF] = \frac{2}{3} = 0.66$$

Assume that the evaluation agent considers the trust to have an importance (I) of 2. Using trust and certainty values and Eq. (2), we calculate the local confidence values for D1 and D2 as follows:

$$Conf_{E,a} = 2 * Trust_{E,a} * Cert_a$$

$$Conf_{E,D1} = 2 * 1 * 80/100$$

$$Conf_{E,D2} = 2 * 0.66 * 75/100$$

$$Local\ Conf_{E,D1} = 160\ and\ Local\ Conf_{E,D2} = 99.$$

5.2.2. Calculating the global confidence

The EVA collects the trust and certainty evidences from the environment. In this example, we assume two positive evidences needed for certainty of diagnosing agents (D1 and D2): (i) checking the blood pressure of a patient agent and, (ii) checking the agent's response to drugs.

- Testing blood pressure. If a diagnosis agent checks the blood pressure of every visiting patient agent, this gives an evidence about agent certainty, and the EVA agent assigns the value for this factor as 1.
- Observing a patient agent responding to drugs. If the diagnosis agent (D1 or D2) observes the patient responding to drugs through diagnosing, this gives an evidence about his certainty of his diagnosing, EVA assign the value for this factor as 1.

We assume that the following table contains the evidences of certainty with satisfying factors that are collected by EVA.

Table 2
Evidences of agent certainty.

Agent	Evidence 1 (testing blood pressure)	Evidence 2 (observe patient responding to drugs)
Agent D1	1	1
Agent D2	0	1

From Table 2, the value 1 means that there is an evidence about agent certainty, 0 means there is no evidence about agent certainty. The EVA calculates the certainty by computing the certainty factors' values to get the certainty value. Based on Eq. (7), certainty is calculated as follows:

$$Cer_{D1} = \frac{1 + 1}{2} = 1,$$

$$Cer_{D2} = \frac{0 + 1}{2} = 0.5$$

The EVA agent confirms the EA agent with the evidence of agents certainty values by the CONFIRM operator as follows:

CONFIRM. Agent 1 (D1): Certainty-Evidence (1).

CONFIRM. Agent 2 (D2): Certainty-Evidence (0.5).

For calculating the trust value, the EVA checks the connections between agents and the strength of these connections. In this example, we assume the connections are represented by connections between each of D1 and D2 and their medical staff. Table 3 contains the opinions of three medical staff agents a_1 , a_2 , and a_3 on D1 and D2. For each reputation value, there is a Duration of Relationship between each of D1 and D2 and the medical staff agents. We assume that there are four values for reputation: 1 = no trust, 2 = low trust, 3 = trust, and 4 = high trust.

EVA calculate the trust value by using Eq. (6) for D1 as follows:

$$WR_{D1,a1} = 10 * 3 = 30$$

$$WR_{D1,a2} = 3 * 1 = 3$$

$$WR_{D1,a3} = 6 * 4 = 24$$

Hence, the total trust value for D1 = $30 + 3 + 24 = 57$.

Similarly, EVA calculate the trust value for D2 as follows:

$$WR_{D2,a1} = 4 * 4 = 16$$

$$WR_{D2,a2} = 5 * 3 = 15$$

$$WR_{D2,a3} = 2 * 3 = 6$$

Hence, the total trust value for D2 = $16 + 15 + 6 = 37$.

An EVA agent confirms with EA the evidence of agents trust values by the CONFIRM operator as follows:

CONFIRM. Agent 1 (D1): Trust-Evidence (57).

CONFIRM. Agent 2 (D2): Trust-Evidence (37).

At this point, EA can calculate the global confidence values for D1 and D2. Based on Eq. (2), the global confidence values are calculated as:

$$Conf_{E,a1} = I * Trust_{E,a1} * Cert_{a1}$$

$$Conf_{E,D1} = 2 * 57 * 1.00$$

$$Conf_{E,D2} = 2 * 37 * 0.50$$

Table 1
Agent's diagnosis results with trust factor values and certainty.

Agent	Opinion (diagnosis)	Years of service (max. 30 years)	Scientific degree	Wrong diagnosis rate	Certainty (provided by agent) (%)
Agent D1	Hart failing	15	PhD (2)	20/120	80
Agent D2	Diabetes mellitus	10	Master (1)	5/50	75

Table 3
Agent's reputation with length of relation.

Agent	Agent a ₁ 's opinion about D1 reputation	Duration of relationship (years)	Agent a ₂ 's opinion about D1 reputation	Duration of relationship (years)	Agent a ₃ 's opinion about D1 reputation	Duration of relationship (years)
Agent D1	3	10	1	3	4	6
Agent D2	4	4	3	5	3	2

$Conf_{E,D1} = 114$ and $Conf_{E,D2} = 37$

By knowing both *LC* and *GC*, *EA* then computes the *Total Confidence* value as follows:

Total Confidence = *LC* + *GC*

Total Confidence (*D1*) = 160 + 114 = 274

Total Confidence (*D2*) = 99 + 37 = 136

The results show that the confidence value of *D1* is greater than *D2*. The implication of these results are many. For example, these results could be used to resolve a conflict between *D1* and *D2* favoring *D1* since it has a higher confidence value. For a problem solving issue, opinion of *D1* is more favorable than *D2*.

5.2.3. Discussion

This study presents a novel model of confidence for open agent systems. The main contribution of this work is a new definition of confidence, especially as it underlies a variety of multi-agent applications. Aside from using a different definition of confidence on the basis of three factors, namely, trust, certainty, and evidence, our approach is different from related ones in a significant way. While other techniques aim to identify trust or uncertainty, our approach considers several related and important factors for confidence in general.

Our proposed model assesses the confidence of each opinion individually on the basis of certainty, trust, and evidence. By contrast, current approaches do not combine these three factors in calculating confidence. The main technical contribution of our work is the management of the duality of trust, certainty, and evidence spaces in a manner that provides a rigorous basis for combining confidence reports.

Calculating confidence is developed in a way that allows the use of missing data in case that information for one of the confidence factors cannot be detected. However, the more data are available, the more accurate is the confidence value.

Furthermore, current approaches do not differentiate between local and global confidence values. The combination of *GC* and *LC* can verify the confidence detection process and hence improve the reliability of the confidence model. Local confidence is detected based on local certainty, which is in turn detected by the agent itself, and local trust with the use of probability theory. Global confidence is detected based on global trust and global certainty. Global trust is calculated through detection of the value of the agent's reputation according to the interaction density among agents; global certainty is detected based on certainty factors.

In addition, we introduced the importance of the trust concept as an essential factor in calculating confidence; current approaches ignore this concept. This addition results in a model that has the ability to control the value of trust in contrast to certainty in measuring the confidence value. In situations in which the importance of trust is low, confidence can depend on the certainty factor.

An evidence-based notion of trust and certainty must accommodate the effects of evidence and the importance of trust. In calculating confidence, trust and certainty are not equivalent, and the importance of trust gives an additional weight to trust. Many existing approaches rely on subjective assessments of trust. However,

two challenges would be accommodating the combination of evidence with trust and the certainty for calculating trust, and making sense of the importance of trust.

A limitation of this study is in detecting the importance of trust, which might need further investigations which is beyond the scope of this paper.

6. Conclusion and future work

The benefits of introducing confidence into the MAS for decision making eliminate many of the opinions of uncertain agents, which are often untrustworthy. Thus, introducing confidence greatly improves the decision-making process of MAS. An agent can make decisions easier based on the evaluation of the trustworthiness of another agent. Computational trust is a very beneficial addition to the traditional decision theory.

In this paper, we propose a multi-agent confidence model that analyzes confidence factors and gathers evidence from the environment. Incorporating evidential information into a confidence-level strategy is necessary for agents in real world MAS. As agents build their local opinions, the variance in their opinions relies on the information sources and their beliefs. Modeling the confidence of agents is useful in choosing appropriate conflict resolution strategies. This framework allows for adjusting the confidence model to suit any application domain by changing the confidence factors. No such confidence framework has been found in the literature.

This paper describes *AgentOpCo*, which is an aide to existing confidence models and depends on certainty and trust in its design. *AgentOpCo* accomplishes this task by adaptations of the design to include certainty, trust, and external evidence. In our future work we shall examine a procedure for the empirical determination of the trust multiplier, α , which is necessary to produce a near accurate value for the confidence value.

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