Improving the Unreliability of Competence Information

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Improving the unreliability of competence information: an argumentation to apply information fusion in learning networks

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Abstract: Automated competence tracking and management is crucial for an effective and efficient lifelong competence development in learning networks. In this paper, we systematically analyse the problem of unreliability of competence information in learning networks. In tracking the development of competences in learning networks, a large amount of competence information can be gathered from diverse sources and diverse types of sources. Individual information is more or less credible. This paper investigates information fusion technologies that may be applied to address the problem and that show promise as candidate solutions for achieving an improved estimate of competences by fusing information coming from multiple sources and diverse types of sources.

Keywords: competences; learning network; information fusion; automated competence tracking; lifelong competence development; self-directed learning; competence profile; competence proficiency level; evidence record; competence record.

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1 Introduction

In comparison with students in formal learning environments where well-designed curricula and experienced teachers are available, self-directed learners in informal and non-formal learning environments usually lack sufficient support in the planning, performing and evaluating learning activities for achieving specific learning/career goals. Nowadays self-organised learning is increasingly supported by interactive learning environments, semantically enhanced content, social software and so on. The advances of technologies enable self-directed learners to develop lifelong competences in learning networks. A learning network is an ensemble of actors, institutions and learning activities that are interconnected through and supported by information and communication technologies in such a way that the network self-organises (Koper and Tattersall, 2004; Koper et al., 2005a, 2005b; Sloep, 2008). A lifelong learner, as a member of a learning network can play several roles. A learner typically engages in a series of learning activities (e.g., courses, training programs, learning materials, assessment and blogs), to reach a goal, such as acquiring a certain competence. However, s/he can also provide learning activities in the domains where s/he is an expert and wants to share experience and knowledge with other members. S/he can assess the work of other members as a peer, a tutor and an expert. S/he can rate the quality of learning activities and assess whether a performed learning activity is easy, suitable or difficult. As the learning network evolves, more and more learning activities will be accumulated and more and more lifelong learners will be involved in such a virtual learning environment.

However, for a learner with a learning demand, it is hard to get a good overview of all learning possibilities that are available and to identify the most appropriate ones for their needs (Koper, 2006). In order to offer right learning activities to right learners at the right time, the system should have complete, accurate, and reliable information about learners and learning activities. More specifically, the system needs to know learners' competence profiles (a set of competences at a particular level of proficiency) and the required competence profiles and objective competence profiles of available courses and training programs. Whenever a learner has a particular learning goal that can be interpreted in terms of a set of competences with particular proficiency levels, the system can identify competence gaps, seek appropriate peers/partners and select suitable learning activities considering others' experiences in performing related learning activities.

The problem is that automated tracking and management of competence is not easy. In theory, it is difficult to represent, measure and interpret competence because competence is a very big subject complicated by very strong opinions and cultural traditions (Ostyn, 2005). In practise, a lifelong learner may describe his/her personal competence profile or target competence profile higher or lower. As a non-expert in competence assessment, self-assessment and the assessment of other learners, s/he may not accurately reflect on the actual competence state. When s/he performs a learning activity or an assessment offered by other learners, if the associated competence profile of the learning activity or the assessment activity is described improperly, the judgement on his/her relevant competences based on the performance of the learning activity or the assessment may be not appropriate. Moreover, the competence information about the same competence-related object at the same period of time may come from multiple sources and diverse types of sources, which may be inconsistent. As a consequence, the competence information captured in learning networks may be unreliable. The recommendations based on unreliable competence information may be misleading.

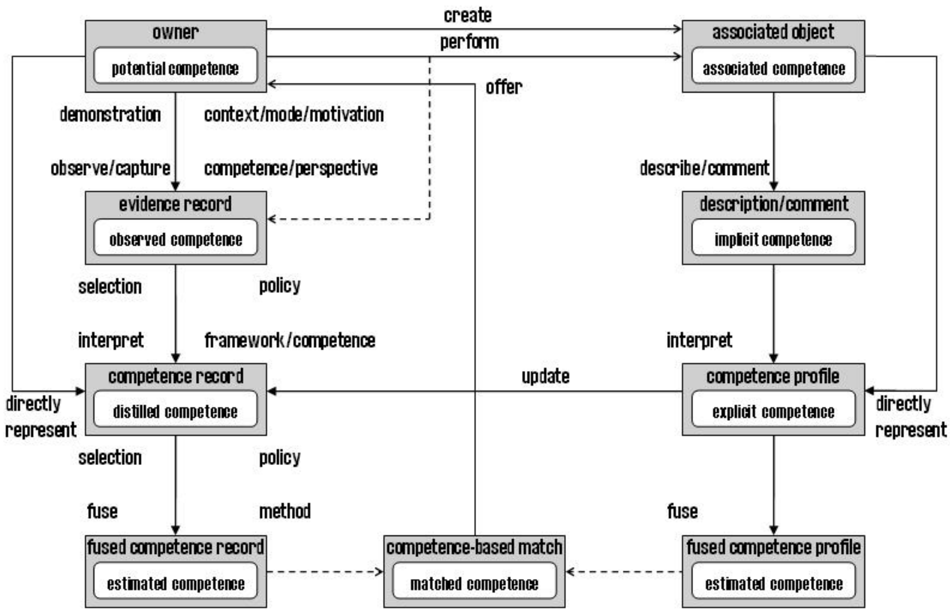
In this article, we first systematically analyse the problem of the unreliability of competence information in learning networks. Then we review the state of art in competence information management and tracking. In order to solve the addressed problem, we propose to adopt information fusion technologies to manage and track competence information in learning networks. We briefly introduce information fusion technologies and investigate how to apply information fusion in learning networks. Finally, we present our conclusions.

2 The problem of unreliability of competence information in learning networks

In this section, we analyse why competence information captured in learning networks may be unreliable. Figure 1 illustrates various forms of competences (represented as inner and white boxes), their carrier (represented as grey boxes), their transformations (represented as arrows) and the main factors that influence the transformation (illustrated beside the arrows) in a learning network.

As shown on the left side of Figure 1, an owner is a person, a team (group), an organisation or a software agent who has potential competences, and is the target to be detected and tracked by the system. Because an owner is usually active in the learning network to create/perform courses/assessment and to observe/interpret competences, sometimes we call an owner (in particular, a person), depending on the context, an actor, a learner, an observer, an assessor and an interpreter. Note that not all software application tools can be regarded as a kind of owners. Certain software agents with certain intelligence that can be used for learners to acquire and assess certain competences at certain levels are owners. Examples of these software agents are intelligent tutoring systems, specific simulators for training and assessment, and latent semantic analysis (LSA) tools. Potential competence is a latent attribute referring to an owner's underlying qualities and characteristics that lead to an effective performance. There is no systematic (objective) method to represent and measure potential competence like we represent and measure colour and temperature. However, potential competence can be demonstrated and observed in a performance. The demonstrated competence can be captured as tangible source (as digital or non-digital evidence, which can be referenced persistently) or intangible source (as memory/impression, which can be recalled). In learning networks, various types of evidence records can be captured, such as a description of a performance (associated with a course, a task/activity or a job), a product (e.g., an article, a design and a response to a questionnaire), and an evaluation (e.g., a certificate, an evaluation of a response to a questionnaire, an analysis report of an article from a LSA tool) (van Bruggen et al., 2004). It is important to note that evidence may or may not precisely reflect the potential competence. The competence owner may demonstrate a particular competence by performing courses/tasks/activities with different characteristics under different situations (context) with different mode/motivation. On the one hand, the potential competence may be higher and lower than those externally demonstrated. On the other hand, a demonstration may or may not be precisely observed and recorded, because observers (or a software agent) may have different perspectives, adopt different measure methods and have different proficiency levels of necessary competences. Thus, observed competences may not precisely reflect the potential competence.

Figure 1 Competence information and transformation



There may be a lot of evidence records relevant to the same competence of an owner, which are originated from the same or/and different performances and provided by the same or/and different observers. A set of evidence records can be used by actors (or software agents) to interpret into a competence record, which explicitly states that an owner has a known proficiency in a particular competence. For example, John's proficiency level of software development is 'expert' or '6'. The process of creating a competence record based on a set of evidence records is called distillation process (Ostyn, 2005). The reliability of a competence record depends on which evidence records are selected and how these evidence records are interpreted. Various policies can be used to select evidence records such as recent evidences, certain types of evidences, particular evidences from excellent/bad demonstrations and the evidences provided by particular actors. In addition, various competence frameworks and criteria can be used to interpret evidences. That is, the proficiency levels of a competence and corresponding indicators are defined differently. Different communities of practise may map the components and/or facets of a competence in different ways (e.g., different roll-up patterns and weighting patterns). For example, John has developed a software tool. According to this performance, his proficiency level of software development is evaluated as 'expert' in the education technology community, but might be represented as 'knowledgeable practitioner' in the software engineering community. In addition, in the software engineering community, the knowledge about the 'design and analysis of algorithms' may be an important component of the competence of software development, but may be not the same (at least, with a less weight in importance) in the educational technology community. Moreover, even in the same community, different people may have different interpretations to the same set of evidence records. The same person may have different interpretations to the same set of evidence records at different time/situations or may change his/her interpretation as his/her relevant competences are improved. As a consequence, there may be a lot of competence records relevant to the same competence of the same owner in the learning network. The interpretation issue has been discussed in detail in Prins et al. (2008). Note that a competence record may be created by oneself in a self-evaluation as a personal competence profile or by someone else (e.g., supervisor and human-resource manager) as an official evaluation based on memory, an intangible source. In such cases, the reliability of competence records depends on whether the memory is good and how the impression is recalled and interpreted. Therefore, there may be a large amount of competence records about each competence of the owner in a competence tracking and management system if it captures and stores all relevant information in a long period of time. The distilled competences may or may not precisely reflect the observed competences.

As shown on the right side of Figure 1, some kinds of objects such as courses/training programs, activities/assessments/tasks or jobs/functions are associated with certain competences. For example, a course or a training program is usually associated with some required competences and objective competences at certain proficiency levels. A task or an assessment is designed for learners to acquire or evaluate certain competences at certain proficiency levels. Like the potential competences of an owner, the associated competences of these objects can not be directly measured. However, they can be evaluated, described and commented as implicit competences captured by the system as descriptions, comments and ratings. Note that these objects may have competence profiles (for example, job competence profile and objective competence profile of a course) that are claimed directly by the creator of the objects or interpreted by someone else. The problem is that different people may describe the same competence-associated object differently. For the same course, somebody may say that the claimed competence proficiency level is higher than the actual one and the others think the course is too difficult for the learners with the required competences with the required proficiency levels.

As illustrated in the three boxes in the bottom of Figure 1, one objective of the learning network is to offer suitable opportunities for the learner based on creating a set of good matches from the personal competence information to the competences information of associated objects. That is, the system has to use certain competence information as estimated competence, which is believed as the most closed to the potential competence and regarded as a reliable competence record, no matter whether it is a self-claimed personal competence, a performance of a course, a result of online questionnaire, a 360 degree assessment or a combination of some of them. The process of transforming distilled competence into estimated competence is fusion. Without a question, the policy used to select competence records and the method used to produce the estimate will influence the value of the fused competence record. Similarly, the fused competence record of the competence-associated objects is influenced by the selection policy and the fusion method. If the estimated competences of the owners and the estimated competences of the associated objects do not reflect the potential competences and the associated competences, respectively, the so called 'matched' competences will not be correct matches.

In summary, competences are transformed in the learning networks and some factors influence the transformation processes. The following factors have influence on the reliability of competence information: the characteristics of a task/activity performed, the context in which a performance is demonstrated, the proficiency levels of the necessary competences of the observer, the policy used to select evidences, the competence frameworks used in interpretation and the proficiency levels of the necessary competence of the interpreter. As a consequence, individual competence records may or may not be credible and trustworthy. In addition, an owner may demonstrate a given competence at different times in different manners and each demonstration may be observed and interpreted by many actors at different time for different purposes. A vast amount of competence information may come from different sources and diverse types of sources. It is a challenge for a competence tracking and management system to produce an appropriate estimate of competence based on a huge amount of competence information, which may be inconsistent and conflict.

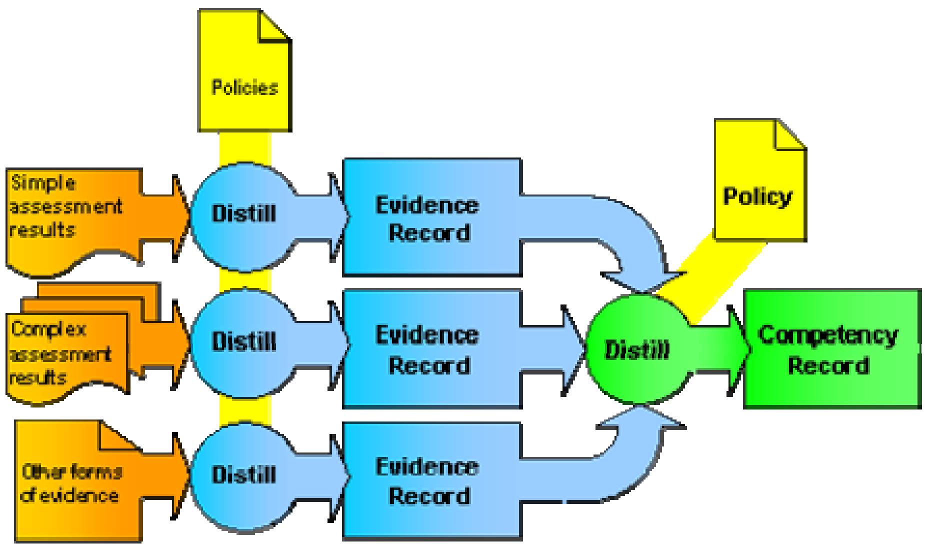
3 State of the art

In order to support the interoperability and reusability of competence information, standard data models and schemas have to be defined. The initial work, including the development of HR-XML (HR-XML, 2004) and the IEEE reusable competency definition (IEEE RCD, 2005), has been based on the IMS reusable definition of competency or educational objective (IMS RDCEO, 2002). Further competence models and specifications have been proposed (Ostyn, 2006; De Coi et al., 2007). These standards and specifications define data models for describing, referencing and sharing competency definitions, primarily in the context of online and distributed learning. These standards and specification have been used by some systems and projects (e.g., TRACE) for enabling interoperability.

However, the problem of unreliability of competence information has not been addressed sufficiently so far. For example, the TRACE project did not deal with the fusion issue. In the TENCompetence project (TENCompetence project) the fusion problem is handled by adopting a time-based method. According to the Domain Model (TENCompetence domain model), when an actor gets registered with a set of evidences (such as certificates, assessment results, products, etc.) in his portfolio (acquired in different learning networks), a positioning service will map these evidences to estimate the proficiency levels of the competences in one of the competence maps in the current learning network. Then, whenever an actor performs a designed learning activity or assessment activity that has its objective proficiency level, if this activity is successfully completed, the relevant proficiency level of the actor will be automatically updated if the previous level was lower than the objective proficiency level. This automatic mechanism can timely trace the competence development without adding human users' burden to do assessment work. The fusion process of this method takes only the newest competence record into account. Using this method implies that the associated competences of all learning activities and assessment activities in the learning network are appropriately described and they are equally credible and trustworthy. If the objective proficiency level of one activity is described higher than the actual associated competence, after a learner successfully performs this activity, the competence estimate of the learner will be updated to a level that may be higher than the level of potential competence. If this inappropriate estimate is used by the system, the relevant recommendations may be not suitable for the learner.

Ostyn (2005) attempted to solve this problem by proposing a concept of distillation of competence information. According to his approach (see Figure 2), a confidence rating is introduced to qualify the evidence record and the competence record. The confidence rating is pre-determined according to a policy. An example policy was given that specifies the confidence ratings to apply for various types of evidence as shown in the Table 1. Adopting this method, an evidence record or a competence record with a higher confidence rating according to the policy will be selected as the competence estimate and others will not be taken into account. For example, the results of a properly conducted 360 degree assessment (rating = 0.75) are more credible than an assessment result from a supervisor (rating = 0.7), and in turn, this result is more credible than that from a self-assessment (rating = 0.1) or an online assessment on an unsecured computer somewhere on the internet (rating = 0.2).

Figure 2 Summary of the competency evidence distillation process (see online version for colours)



Source: Ostyn (2005)

However, it is hard to say that a pre-defined, source-type-based policy is suitable for all concrete cases. For example, sometimes the result of a self-assessment may be more appropriate (closer to the potential competences) than an assessment result from the supervisor. Using 360 degree feedback, the assessors involved in the same assessment may have inconsistent and even conflict assessment results on the same competence. As a consequence, the final result of a concrete 360 degree feedback may be not very credible and trustworthy. In addition, if several competence records have the same confidence rating (for instance, the confidence ratings of four source types are defined in Table 1 as 0.7), but they state different proficiency levels, which one should be selected as the final result? This approach, in fact, simply trusts a source according to the type of the source, no matter whether the individual source is credible and trustworthy. Once a record is selected, all other records coming from other sources will be ignored, without analysing whether individual sources are credible or not according to the historical records of the sources. Therefore, this approach can not effectively solve the problems of unreliability.

Table 1 Summarising a sample confidence policy

Evidence source type	*Rating*	*Comments*
Resume statement, unverified	0.1	Self rating is better than nothing.
Online assessment, no authentication	0.2	Anyone might stand in for the person or team to be assessed.
Online assessment, identity verified	0.5	Proctoring ensured that there was no stand-in.
Peer assessment	0.5	
Online assessment with certified validity, identity verified	0.7	High quality, scientifically validated assessment.
Resume statement, verified by HR	0.7	
Supervisor	0.7	Supervisor may have personal issues clouding judgement.
Training instructor	0.7	Performance in training situation may not be entirely reliable.
360 degree, unaudited	0.75	
360 degree, audited	0.9	
HR director	0.95	
Executive	1.0	Trumps everything else

Source: Ostyn (2005)

In this paper, we will investigate whether an information fusion approach is suitable for solving the problem of unreliability of competence information.

4 Introduction of information fusion

The concept of information fusion (including data fusion and decision fusion) is easy to understand and the operation of information fusion by itself is not new. As stated in Wald (2001), the human being has the capability to use multiple senses to percept the environment. Rich information is acquired from various sensory organs such as eyes, nose, month, ears, tongue and hands. In addition, a man has redundant sensors. Two eyes have slightly different viewing angles, making possible stereo vision and depth perception. If one eye is disabled, vision is still possible, though in a degraded mode. The brain processes the acquired information using additional sources of information: its memory, its experience and its a priori knowledge. Calling upon its reasoning capabilities, the brain 'fuses' all this available information to produce estimates about objects of interests, to assess situations, to make decisions, to update knowledge and to direct actions.

However, information fusion, as a technique, is relatively new. It is multi-disciplinary by essence and is at the crossing of several sciences. According to Wald (1998, 1999), information fusion is 'a formal framework in which are expressed the means and tools for the alliance of data originating from multiple and diverse sources'. Steinberg (2001) viewed information fusion as a process of combining data or information to estimate or predict entity states. The data range from numerical measurements to verbal reports. Some data cannot be quantified; their accuracy and reliability may be difficult to assess. Information fusion aims at achieving improved accuracies and more specific inferences that could not be achieved by the use of any single source alone (Hall and Llinas, 1997).

The information fusion offers some advantages (Waltz and Llinas, 1990):

- Robustness and reliability: The system is operational even if one or several sources of information are missing or malfunctioning.
- Extended coverage in space and time: The system can detect and trace the dynamic changes of the entities because a variety of distributed sensors can acquire information about the same entity at different time in different places.
- Improved confidence: The use of redundant and complementary information increases the certainty.
- Reduced ambiguity: More complete information provides better discrimination between available hypotheses.
- Providing a solution to process the vast amount available information for many complicated application systems.

The application of information fusion in technical systems requires mathematical and heuristic techniques from fields such as probability and statistics, Bayesian decision theory, plausibility theory, pattern recognition, fuzzy logic, neural network, expert systems, cognitive psychology, information theory and decision theory. The functional application of information fusion is grounded in mathematical theories which are beyond the scope of this paper. The interested reader is referred to Hall (1992), Waltz and Llinas (1990) and Varshney (1995) for a detailed mathematical discussion. Information fusion is useful for several objectives such as detection, recognition, identification, tracking and decision making. These objectives are encountered in many application domains such as defence, robotics, medicine, space, transportation and weather forecast.

In order to have a better understanding of information fusion technologies, we briefly introduce one of its applications in military with wireless sensor networks (WSN), a special type of ad hoc network composed of a large number of nodes equipped with different sensor devices (Akyildiz et al., 2002; Nakamura et al., 2007). In comparison with large and powerful sensors that are usually deployed in positions far from the battlefield and are definitely the targets being attacked by the opposing forces, the sensors in a WSN are small and inexpensive with limited sensing, computation and communication ability. They are prone to failures and the information received from a single sensor may or may not be credible and trustworthy. There are different types of sensors such as seismic, low sampling rate magnetic, thermal, visual, infrared, acoustic sensors and radar, which are able to monitor a wide variety of ambient conditions. However, as a system, a WSN can collect and analyse information coming from all sensor nodes distributed in the area in real-time. According to the characteristics of the different types of sensors and the specific characteristics (e.g., location) and historical behaviours of each sensor, the system will make judgements on the targets to be traced and on the reliability of data sources. If the system is well developed, it can constantly monitor the status of the friendly troops, the condition and the availability of the equipment and the ammunition in a battlefield. They can closely watch for the activities of the opposing forces and some valuable, detailed and timely information about the opposing forces and terrain can be gathered. They can detect and track targets of the opposing forces (such as tanks, planes and missiles) and can be incorporated into guidance systems of the intelligent ammunition. As the operations evolve and new operational plans are prepared, new sensor networks can be deployed anytime if necessary. Because any information fusion application is a complicated system with a lot of domain-specific knowledge and mathematics, it is impossible to present a complete and detail example in this paper.

5 Competence information fusion

Generically speaking, some objectives such as detection, recognition, tracking and decision making will be encountered to automatically track competence development in learning networks. As described in Section 2, a lot of competence information can be gathered from multiple sources and diverse types of sources. In particular, a learner can acquire competence by assessing and by being assessed. The assessment conducted by experienced assessors and a certification organisation will be used by the system as somewhat standards for analysing the accuracy and reliability of judgements made by ordinary learners and then judging the credibility of the learners at a given proficiency level of a certain competence. Moreover, even if a learning activity is not appropriately described (in terms of required/objective competences at certain proficiency levels), an improved estimate may be produced through analysing the performance and the ratings (e.g., easy/suitable/difficult) of many learners with comparable proficiency levels. For example, if learners with validated and required proficiency levels rate a learning activity as too difficult and most of them can not successfully complete it, it is necessary to analyse whether the required/objective competences of the learning activity are lower than the actual ones. In this paper we briefly analyse similarities of WSN and learning networks from the perspective of application of information fusion technologies. Then we introduce the basic idea of fusing competence information in a learning network by presenting a scenario.

We first analyse the similarities between a WSN and a learning network in the following aspects:

- In a WSN, the targets to be detected and tracked in military applications are objects such as tanks, planes and missiles. An object has static properties (e.g., size, shape and colour) and attributes (e.g., position, direction and velocity). There exist actual data if the object is moving in the battlefield. However, it is difficult to precisely measure the properties and attributes in the battlefield, where many factors (e.g., distance, perspective, bad natural conditions and military operations) influence the measurement. In particular, the object may be made with a designed shape, special material and equipments to protect and hide it from being detected. In a learning network, the object to be detected and tracked is the lifelong learner with a set of potential competences. Each competence has an actual proficiency level at a given time. As mentioned already, competence is difficult to be precisely measured because many factors influence the accuracy of the competence records.

- In a WSN, a detected object is represented as a set of measurements, or attributes, or rules describing the object, completely or not. The goal is to produce an estimate of the values of properties and attributes, which are as close as possible to the actual data and then to make a correct judgement on the object. In a learning network, a competence profile is used to represent all competences. Each competence profile item can be represented as an estimate of a certain competence.
- In a WSN, a sensor is a measurement device and an imprecision value is usually associated with its observation. In addition, the sensing capability of a node is restricted to a limited region. Moreover, a given type of sensors can only perceive certain properties of the target. In a learning network, lifelong learners and software agents (e.g., LSA tools and assessment-specific simulators) are involved in competence assessment. The capability and the time available of each agent (a human agent or a software agent) are limited and some agents may have conventions and bias.
- In a WSN, the data gathered by sensors are more or less credible and trustworthy. In order to overcome sensor failures, technological limitations, spatial and temporal coverage problems, multiple sensor nodes (with various types) will be deployed fully covering a region of interest. Each sensor obtains a partial view of a target under observation in a certain location at a certain time. These pieces of view can be fused into a continuously changed trace of the target. The redundant observations and measurements of multiple sensors can be fused to obtain more accurate estimate. Different types of sensors can perceive different properties of the target and the complementary information can be fused to produce a complete perception. In a learning network, a given competence of an owner can be assessed by oneself, peers, experienced people, software agents and certification organisation based on a performance. Individual assessment may or may not be credible and trustworthy. If the system arranges necessary and sufficient assessments to collect information about the competence on various aspects, at different times, from diverse types of assessors, as the actor works within a learning network for a period of time, massive competence information about the same the actor will be captured. The competence state of the actor in different development phases will be fused into a continuously changed trace.

The analyses of the similarities reveal that information fusion may be a promising technical approach to the problem of unreliability of competence information in learning network. However, if we want to develop an automated competence tracking and management system, we will face a formidable set of hurdles, all of which should be taken. This paper discusses one of the primary technical issues concerning the unreliability of competence information. In general, fusion requires appropriate weighting of information based on the quality of the source of the information. A credibility model is needed to characterise the quality of information based on the source and the circumstances under which the information is collected. If a new competence record is collected, it is necessary to rate separately the quality (reliability) of both the source that produces the competence record and the content of the competence record itself. In practise, if the source is judged 'unreliable', the competence record is essentially discarded. If the source is judged 'reliable', then the content of the competence record is evaluated. Then the system decides how much trust should be given to it. Usually, a computational model is used to update the current competence estimate by using prior information and evidences. It is needed to compare the competence record and the current competence estimate. If the conflict is small, it means the record fits with previous opinion and thus seems to reinforce the estimate. If the conflict is large, it means that the content of the record clashes with the previous opinion. It is needed to find out the origin of the clash and try to resolve it.

For a better understanding of the fusion process, we present a fictitious scenario. John has learnt software engineering with a learning network for years and his competence on software development was estimated as 'knowledgeable practitioner'. He recently developed a software tool and published it in the learning network. Sam is a newcomer in the learning network and he claims that his competence on software development is 'knowledgeable practitioner'. Then Sam is suggested by the system to assess John's software tool. After inspecting the source code and the relevant documents, Sam judges that John's proficiency level on software development is 'expert'. Because Sam has no history record, the reliability of his judgement on software development at 'expert' level is 0%. Therefore, this competence record is rated as 0% as well. An estimate about John's software development is produced according to Sam's judgement. The value of the estimate is 'expert' and credibility of the estimate is 0%. Then, more competence records about John's software development are collected. These competence records are created by persons who have history records on software development and their reliabilities of judgement on software development at 'expert' level are ranged in between 25% to 38%. Among these competence records, 90% of the people judge that John's software development is 'expert' and only 10% people judge that his level is 'practitioner'. According to a computational model, the estimate about John's software development is still 'expert', but the credibility of the estimate is increased to 32%. This increase results in the change of Sam's reliability of judgement on software development at 'expert' level (from 0% to 16%). At the same time, the credibility of Sam's claim that his competence on software development is 'knowledgeable practitioner' is 15%, although he has not taken any relevant course on software development in the learning network so far. After that, another competence record is collected that judges John's level as 'practitioner'. It is created by Joseph who is reliable (92%) on judging software development competence at 'expert' level. Obviously something with the belief functions is wrong. It is necessary to check whether the pressure to change is higher than the resistance parameter. As more competence records support Joseph's judgement and these competence records are created by people with higher reliabilities (ranged from 83%–94%), the pressure to change is increased and finally it is higher than the resistance parameter according to the computational model; the credibility of the judgements and the sources, which were used to develop the previous estimate, will be re-checked. If the conflict is because they use different competence frameworks and they work in different communities (in this case, one community is educational technologies and the other is software engineering), then the system recognises that the ‘expert’ level in the educational technology community roughly equals to ‘practitioner’ level in the software engineering community. There is no need to change the credibility of the judgements and the reliabilities of the sources. Otherwise, if they use the same competence framework and it is proved that the new judgements are much more reliable, the fusion process results in a revision of the current belief functions. For example, the reliability of all people who support Sam’s judgement will decrease and the reliability of all people who support Joseph’s judgement will increase. Because there are very complicated inter-relationships among the competence information in a learning network, one change may trigger a sequence of changes. For example, because the reliability of a person has been changed in this case and this person has been involved in evaluating other learners’ software development at ‘expert’ level, this change will influence the competence estimates of those learners.

How to change the credibility and propagate the changes is an issue of the design of the computational model and the relevant algorithms. A large variety of models and algorithms have been proposed by the information fusion community. We propose to launch research to apply and develop models and algorithms to fuse competence information in learning networks. We feel that the fusion problem in learning networks may be more complicated than that in traditional application domains in some aspects, because the ‘sensor’ is usually human being in a learning network.

6 Conclusions

We analysed the problem of unreliability of competence information gathered in learning networks. We presented a model about different forms of competence and their transformations in a learning network. Some factors influence the reliability of competence information: the characteristics of a task/activity performed, the context in which a performance is demonstrated, the proficiency levels of the necessary competences of the observer, the policy used to select evidences, the competence frameworks used in interpretation and the proficiency levels of the necessary competence of the interpreter. In order to address the problem of unreliability, we briefly introduced information fusion as a technique that may help in solving the problem we are bound to encounter once we implement automatic competence tracking and management in learning networks. We analyse the similarity between a WSN and a learning network and conclude that information fusion shows promise as a candidate solution to the problem of unreliability of competence information. We believe that a great deal of research is needed to introduce, implement and leverage the concept of competence information fusion in order to make an organisational impact.

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References

Akyildiz, I.F., Su, W., Sankarasubramaniam, Y. and Cayirci, E. (2002) 'Wireless sensor networks: a survey', *Computer Networks*, Vol. 38, pp.393–422.

De Coi, J.L., Herder, E., Koesling, A., Lofi, C., Olmedilla, D., Papapetrou, O. and Siberski, W. (2007) 'A model for competence gap analysis', *WEBIST 2007*, *Proceedings of the Third International Conference on Web Information Systems and Technologies: Internet Technology/Web Interface and Applications*, Barcelona, Spain, March 2007, INSTICC Press.

Hall, D.L. (1992) *Mathematical Techniques in Multisensor Data Fusion*, Artech House, Boston, MA.

Hall, D.L. and Llinas, J. (1997) 'An introduction to multisensor data fusion', *Proceedings of the IEEE*, Vol. 85, No. 1, pp.6–23.

HR-XML (2004) 'Measurable competencies', available at http://www.hr-xml.org, accessed on August 2004.

IEEE 1484.20.1/Draft – Draft Standard for Reusable Competency Definitions (RCD) (2005) November, available at http://ieeeltcs.org/wg20Comp/Public/IEEE_1484.20.1.D3.pdf.

IMS Reusable Definition of Competency or Educational Objective (RDCEO) (2002) October, available at http://www.imsglobal.org/competencies/.

Koper, R. (2006) 'Building learning networks for lifelong learners: challenges, models, technologies and standards', *Proceedings of the ICALT 2006* (a tutorial).

Koper, R. and Tattersall, C. (2004) 'New directions for lifelong learning using network technologies', *British Journal of Educational Technology*, Vol. 35, No. 6, pp.689–700.

Koper, R., Giesbers, B., Van Rosmalen, P., Sloep, P., Van Bruggen, J., Tattersall, C., Vogten, H. and Brouns, F. (2005a) 'A design model for lifelong learning networks', *Interactive Learning Environments*, Vol. 13, No. 1–2, pp.71–92.

Koper, R., Rusman, E. and Sloep, P. (2005b) 'Effective learning networks', *Lifelong Learning in Europe*, Vol. 1, pp.18–27.

Nakamura, E.F., Loureiro, A.A.F. and Frery, A.C. (2007) 'Information fusion for wireless sensor networks: methods, models, and classifications', *ACM Computing Surveys*, Vol. 39, No. 3, Article 9, 55pp.

Ostyn, C. (2005) 'Distilling competency information', White Paper, available at http://www.ostyn.com/rescompetency.htm.

Ostyn, C. (2006) 'Simple reusable competency map proposal (SRCM)', available at http://www.ostyn.com/resources.htm, February 2006.

Prins, F.J., Nadolski, R.J., Berlanga, A.J., Drachsler, H., Hummel, H.G.K. and Koper, R. (2008) 'Competence description for personal recommendations: the importance of identifying the complexity of learning and performance situations', *Journal of Educational Technology & Society*, Vol. 11, No. 3, pp.141–152.

Sloep, P.B. (2008) 'Building a learning network through ad-hoc transient communities', *International Conference on Computer Mediated Social Networking (ICCMSN)*, Dunedin, New Zealand, 11–13 June 2008, available at http://hdl.handle.net/1820/1198.

Steinberg, A.N. (2001) 'Data fusion systems engineering', *IEEE Aerospace and Electronic Systems Magazine*, Vol. 16, No. 6, pp.7–14.

TENCompetence domain model, available at http://dspace.ou.nl/handle/1820/649.

TENCompetence project, available at http://www.tencompetence.org.

TRACE project home page, available at http://trace.education-observatories.net/.

van Bruggen, J., Sloep, P., van Rosmalen, P., Brouns, F., Vogten, H., Koper, R. and Tattersall, C. (2004) 'Latent semantic analysis as a tool for learner positioning in learning networks for lifelong learning', *British Journal of Educational Technology*, Vol. 35, No. 6, pp.729–738.

Varshney, P. (1995) *Distributed Detection and Data Fusion*, Springer-Verlag, New York, NY.

Wald, L. (1998) 'An European proposal for terms of reference in data fusion', *International Archives of Photogrammetry and Remote Sensing*, Vol. 32, Part 7, pp.651–654.

Wald, L. (1999) 'Some terms of reference in data fusion', *IEEE Transactions on Geosciences and Remote Sensing*, Vol. 37, No. 3, pp.1190–1193.

Wald, L. (2001) 'Introduction to information fusion', available at http://www.data-fusion.org/article.php?sid=64.

Waltz, E. and Llinas, J. (1990) *Multisensor Data Fusion*, Artech House.