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Influence of Terrain on Modern Tactical Combat: Trust-based Recommender System

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ABSTRACT

In Army Services, there are a number of valuable decisions that have to be taken for mission accomplishment. These decisions are very important and the choice of a weapon may be able to alter the outcome of a battle decisively. Among several such decisions one is to decide which weapons to deploy/assign over a given terrain. Recommender systems are intelligent applications to assist users in a decision-making process where they want to choose one item amongst a potentially overwhelming set of alternative products or services. This paper proposes the design of recommender system that automates the process of finding the appropriate type of weapon(s) that can be deployed over a terrain having certain characteristics. The user agent seeks recommendations, which are in the form of intuitionistic fuzzy set (IFS), from trustworthy peers and produces aggregated order of recommendations taking degree of trust on recommenders into consideration. Trust on recommender is also updated based on importance of recommendation given to the user. A prototype of the trust-based recommender system for modern tactical combat system has been designed and developed through which the user can get the recommendation to use a specific kind of weapon or a set of weapons that would be best-suited in a given type of terrain.

Keywords: Recommender systems, trust, clustering, intuitionistic fuzzy set, agent, tactical combat

1. INTRODUCTION

As information mounts, it leads to the problem of how to access, navigate through, and select available options. One possible solution to this information overload problem is based on recommender systems or the concept of automatic recommendation generation. A recommender system recommends items to users by predicting items relevant to the user, based on various kinds of information including items, user information and interactions between users and items[11-13].

Recommender system forms a specific type of information filtering technique that attempts to present information items such as movies, music, books, news, images, web pages, that are likely to be of interest to the user. Typically, a recommender system compares the user's profile to some reference characteristics. These characteristics may be from the information item (the content-based approach) or the user's social environment (the collaborative filtering approach) or a combination of both (Hybrid-filtering approach)[2,7,8]. These systems are very powerful cognitive decision-makers in the context of distributed online information processing in real-time networked scenarios[1]. This would be considered a highly desirable feature in the context of military databases that are almost always networked when quick and valid solutions are needed in varied combat situations

Recommender systems have now evolved to trust–based recommender systems where the trust component has been modelled using soft computing techniques. Thus, the recommender systems have graduated from being intelligent decision–support systems to human–level artificial intelligence (AI) systems. Trust plays an important role in the decisions related to sources that are used by human to take recommendations. They do not go out on the street and just start taking recommendations from anyone on the street, but opt for trustworthy acquaintances to suggest them products. In real life, these use the data provided by others, but process it according to their own reasoning power, into information that they use for decision-making. If recommender system also use advice-seeking and decision-making process similar to real life, then it will be easier for the user to trust the recommendations of the system. Hence, by adding a trust component to a decentralised environment, the problem of lack of trust on the recommenders is alleviated.

In Army Services, there are a number of domain experts (at different command levels) each having knowledge of his domain according to his own perspective. Now, if the user wants information about the use of strategies and set of weapons that can be deployed in a specific terrain such as desert, he may contact the domain experts who will provide their knowledge of the specific problem area.

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Thereafter, the user will process the information gathered according to his specification. As the experts may be geographically distributed, this knowledge engineering problem is a distributed computing problem.

Research literature on intelligent agent system architectures has established that the problems that are inherently distributed can be efficiently implemented as a multi-agent system. So the prototype proposes the solution based on a multi agent system (MAS) approach, where every user in the prototype is represented by an agent. The agents communicate with others to generate the recommendation.

2. PROPOSED RECOMMENDER SYSTEM

Committing weapons to a given terrain is a part of a larger problem better known as the weapon-target assignment (WTA) problem. The decision to either commit or acquire or both, a weapon or a set of weapons, depends upon a number of factors such that each one of these, either in isolation or in association with the other factors, decide the success or failure of weapon assignment in a complex way. The proposed recommender system is a multi-agent system[15] to suggest set of weapons to deploy/assign over a given terrain that incorporates the social recommendation process based on trust. Most of the existing recommender systems ignore the social elements of decision-making and advice-seeking, and hence the system model does not match the mental model of the user[4-6,10]. Even though the recommender systems may be providing accurate recommendations, studies by Sinha and Swearingen[14] have found that users prefer the recommendations of friends over those of recommender systems. These recommender systems are designed with a central authority controlling the data as well as computational resources to generate recommendations. The user does not know about the people whose tastes are used to suggest items. This acts as a hindrance for the user to trust the recommendations of the system.

The social recommendation process is taken into consideration by forming a network of the agents that act as a society and these agents interact with each other on the basis of trust relationships. These trustworthy relationships form a web of trust[9] as illustrated in Fig.1, which shows such a network of peers represented by the numbered circles, where the numbers in the circles identify the various peers in the application domain. An edge represents that trustworthy relationship exists between the connected agents with certain degree of trust. Every agent maintains a list of peers adjacent to it along with the degrees of trust on them. It is not necessary that if A trusts B with degree of trust as x, then B also trusts A with degree of trust as x.

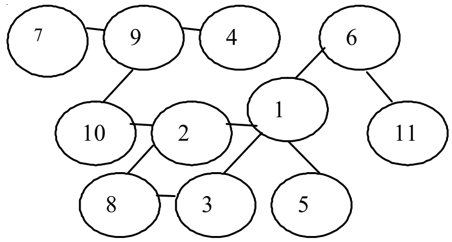

Figure 1. A network of peers represented by the numbered circles.

The peer agents in the community environment exchange recommendations about the products during their idle time, which is being referred to as unintentional encounters.

The proposed recommender system has two different types of agents: user agent (UA), and recommender agent (RA). User agent collects the data from the user using web-based GUI. It captures the information for the attributes to be considered for the selection of a weapon and its degree of significance. User agent also stores trust values for each interacting recommender agent known to it and prioritises the recommender agents according to their trust value.

Once, user agent receives the recommendations from all trustworthy recommender agents in its neighbourhood, it generates the final recommendation list of weapons after taking into account the degree of trust on each of the recommender agent. User agent also updates the degree of trust on each recommender agent after evaluating the recommendations given by them.

The recommender agent after getting a request from user agent generates a set of recommendations to best

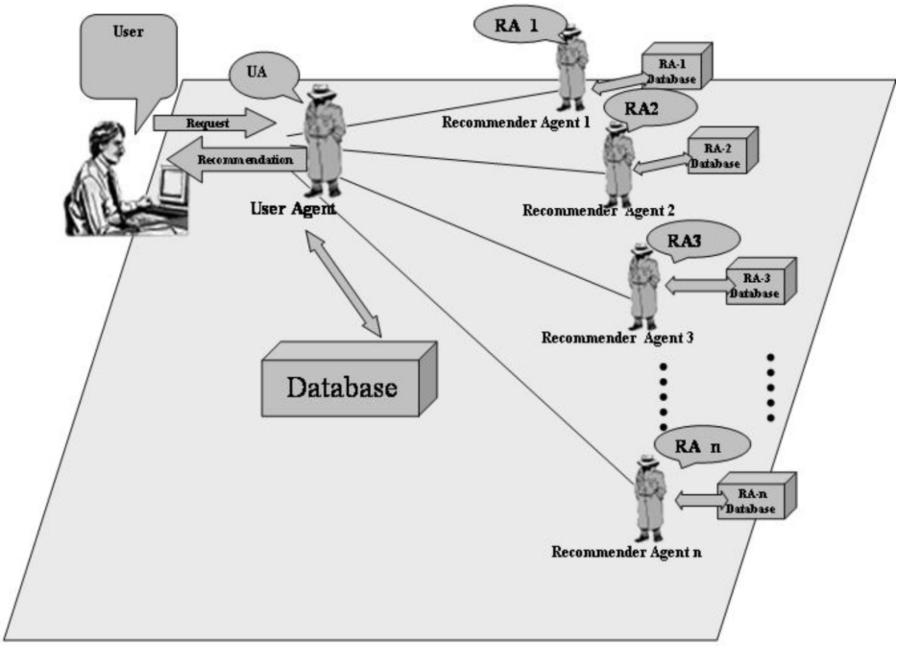

Figure 2. The functional diagram of influence of terrain on modern tactical combat system.

satisfy the incoming request. Every recommendation corresponds to a weapon for a specific weapon category, for a given terrain, and is in the form of IFS[3]. The IFS recommendation for a weapon has a degree of membership (satisfaction), degree of non-membership (dissatisfaction) and the degree of hesitation (uncertainty) signifying the relevance, irrelevance, and uncertainty of the weapon for a given user. To personalise the weapon recommendations according to the taste of the user agent A, the recommender agent maintains the following lists:

- *Preference list*: The preference list, P_A consists of the information in terms of the attributes (weight, armour, power/weight, maximum range, elevation, etc) of the weapons liked by the user in the past connected to user agent *A*. There are separate sublists in P_A corresponding to the attributes weight, armour, power/weight, maximum range, elevation. The order of names of weapons in a sublist in P_A corresponding to a particular attribute signifies their priority in their respective sublists.
- *Uncertain list*: The uncertain list, U_A consists of the same type of information as that of the preference list. However, it is unordered list accumulated during unintentional encounters and the recommender agent has no idea whether the user prefers one weapon over the other.

Every agent in the system maintains a degree of trust and information about the tastes of the agents that are connected to it directly. The recommenders pass only that recommendation to the user agent that matches its taste leading to personalisation of the recommender system. This reduces the number of recommendations that need to be given to the user agent by removing the unnecessary recommendations which further reduces the number of computations that the user agent has to perform at the aggregation of the recommendations to find something useful for itself.

3. TRUST-BASED RECOMMENDATION GENERATION

3.1 Generating Recommendations

Various ways in which a recommender agent recommends a weapon are:

- *Case 1*: The weapon is in the preference list corresponding to the user stored in the recommender agent.
- *Case 2*: The recommender agent comes to know about the weapon through a trustworthy acquaintance during unintentional encounters.
- *Case 3*: The recommender has used the weapon, and feels that the weapon has a general appeal even if it does not conform to the taste of the user. Recommender agent recommends that weapon to the user with the degree of uncertainty. The degree of membership is zero for such weapons and the degree of non-membership is computed using the other two degrees.

The weapons of *Case* 3 are recommended whether these are according to the taste of the user or not. For the weapons of *Case* 1 and *Case* 2, matching is done with P_A and U_A, respectively and based on the matching results, the recommendations are generated.

3.2 Intuitionistic Fuzzy Set Generation for Weapons

A recommender can recommend weapons known to it. The recommender agent comes to know about the weapon either through usage or through unintentional encounters. During the unintentional encounters, an agent exchanges the information about only those weapons that it has used and is satisfied with.

An agent stores the names of the weapons experienced earlier. When an agent has to generate recommendations for other agents, it retrieves knowledge about the experienced weapons.

Let a weapon *W* be represented by *n* attributes (a_1, $a_2 \ldots a_n$). A weapon *W* is suggested to the user agent *A*, along with the IFS generated for it as shown below:

The degree of membership of weapon *W*, μ_w is computed using the preference list P_A, as:

For every attribute a_i ($i = 1, \ldots, n$) of weapon *W*, do the following:

Search the position p_i of weapon *W* in preference list P_A then compute the rank Rank_i as the normalised position of *W* in the range [0 to 1] using the following formula:.

$$\text{Rank}_i = 1-((p_i - 1) / (\max-1))$$

where max represents total number of weapons that exist in P_A

Finally, degree of membership of weapon *W*, μ_w is computed as:

$$\mu_w = \frac{\sum_{i=1}^{n} (da_i * rank_i)}{n}$$

where da_i ($i = 1, 2, \ldots, n$) represents the normalised degree of significance that the user associates with the i^{th} attribute, *n* represents the total number of attributes of weapon *W* in P_A.

The degree of uncertainty of weapon *W*, π_W is computed using the uncertainty list U_A, created during the unintentional encounter among the trustworthy agents and on the experienced weapons of the recommenders that are not matched with weapons of P_A as:

π_W is computed from P_A, using the experienced weapons list by assigning the satisfaction values of *W*, greater than some threshold value.

π_W is computed using the uncertainty list U_A, as: Let k_i be the attribute value of W for attribute a_i in U_A. Compute the degree of uncertainty of the W as:

$$\pi_W = \frac{(da_1 * k_1 + da_2 * k_2 + \ldots + da_n * k_n)}{n}$$

where da_i ($i = 1, 2, \ldots, n$) represents the degree of significance that the user associates with the i^{th} attribute.
n represents the number of weapons in UA.

The degree of non-membership of weapon *W*, ν_W is computed as follows:

$$\nu_W = 1 - \mu_W - \pi_W$$

3.3 Recommendation List Generation by Recommender Agent

After matching the weapons with the preference list and uncertain list, the degree of membership, degree of non-membership and uncertainty is available with the recommender agent for all the weapons that it knows. The following method is used to generate the final list of the weapons that are to be recommended to the user agent along with IFS that is computed for these:

1. All the weapons that are part of *Case* 3, section 3.1 are to be considered for further processing.
2. For all the weapons of *Case* 1 and *Case* 2, Section 3.1, do the following:
   - 2.1 The weapons with non-zero degree of membership are followed by the weapons with non-zero degree of uncertainty.
   - 2.2 Within the weapons with non-zero degree of membership, order the weapons in descending order on degree of membership.
   - 2.3 Within the weapons with non-zero degree of uncertainty, order the weapons in descending order on degree of uncertainty.

3.4 Final Trust-based Recommendation List Generation by User Agent

The user agent needs to form an aggregated list out of the IFS recommendations lists received from the trustworthy recommender agents. User agent has to generate a final consolidated list from all the recommendations that are received from the recommenders. The user agent computes the degree of importance of a weapon on the basis of degree of trust on the recommenders who have recommended the weapon, the relative position of the weapon in the list of recommenders, and the IFS recommendation of the recommender. The user agent generates a final consolidated list from all the recommendations that are received from the recommenders using the following aggregation method:

1. Identify the distinct weapons from the lists and then compute the degree of importance (*DoI*) of every weapon (W_i) as follows:

$$
\begin{aligned}
DoI_i = MAX(&ABS(DoT(R_1) * \{\mu_i(R_1) - \nu_i(R_1) * \pi(R_1)\} * Rank_i(R_1)),\\
&ABS(DoT(R_2) * \{\mu_i(R_2) - \nu_i(R_2) * \pi_i(R_2)\} * Rank_i(R_2)), \ldots\ldots\\
&ABS(DoT(R_k) * \{\mu_i(R_k) - \nu_i(R_k) * \pi_i(R_k)\} * Rank_i(R_k)))
\end{aligned}
$$

where,

$DoI_i(A)$	is the degree of importance of W_i as computed by A
R_j	is the j^{th} recommender
$\mu_i(X)$	is the degree of membership of W_i according torecommender X
$\nu_i(X)$	is the degree of non-membership of W_i according to recommender X
$\pi_i(X)$	is degree of uncertainty or hesitation of W_i according to recommender X
$DoT(R_j)$	is the degree of trust of the A on R_j
$Rank_i(R_j)$	is the normalised position of W_i in the recommendation list of R_j
k	is the total number of recommenders who have recommended W_i

2. Compute the threshold, TDOI for degree of importance as
   TDOI = $\mu - \nu * \pi$
   where, μ, ν, and π are degree of membership, non-membership, and uncertainty, respectively that the user agent expects from the interesting weapon.
3. For all the distinct weapons, W_i of *Step* 1, the degree of importance obtained is a real number that lies between 0 and 1; and hence, there is no need for its normalisation. Arrange the products in the descending order of their degrees of importance.

3.5 Initialising and Updating Degree of Trust on the Recommenders

3.5.1 Trust Initialisation

When a new agent comes up in the system or the system starts from the scratch, then the agents have to initialise the trust values for some of the other agents in the application domain to form its acquaintance set. If an agent is known to the other agent (i.e., the corresponding human know each other), then the human associated with the agent can initialise the degree of trust according to the personal dealings with the person. However, the system also allows an agent to initialise degree of trust on an agent *X*, on the basis of the experiences of the other agents with *X*, i.e., to what extent the other agents in the application domain have received good recommendations from *X*. The degree of trust is then regularly updated on the basis of the personal experience of the agent with *X*.

The new agent *Y*, asks for the experience of known agents' (connected to it) wrt *X*. Let *q* agents return their experience values as the number of good recommendations received to the total number of the recommendations received from *X*. Let j^{th} agent gives the experience as e_j. Then the degree of trust on *X* as computed by *Y* can be written as follows:

$$DoT(X) = \frac{\sum_{j=1}^{q} e_j}{q}$$

If *q* is large, then basically one is interested in finding what the experience of majority of the agents is? Hence experiences in such cases can be clustered and degree of trust can be computed.

3.5.2 Trust Updation

The degree of trust on a recommender is updated on the basis of the distance between degree of importance of the weapon as given in the aggregated list of the user agent (*A*) and the recommendation list of the recommender (*R*). The difference of opinion between the user and the recommender is computed as follows:

$$d = \frac{(D_1 + D_2 + ... + D_P)}{p}$$

where,

$D_i = \{\mu_i(R) - \nu_i(R) * \pi_i(R)\} - \{\mu - \nu * \pi\}$, μ, ν, π; and $\mu_i(R)$, $\nu_i(R)$, $\pi_i(R)$ are as defined earlier. p is the total number of weapons in the recommendation list of R.

Depending upon whether the difference between its aggregated list and the recommendations is below its acceptable threshold d_t or not, the user agent updates the degree of trust, $DoT(R)$ on recommender as follows:

$$DoT(R) = DoT(R) + (d_t - d)$$

Hence, trust increases for those recommenders who give good recommendations and vice versa.

4. EXPERIMENTAL STUDIES

A prototype of the trust based recommender system for modern tactical combat system (ITMTC) was designed and developed using JADE (Java Agent Development Environment), JSP and Oracle 10g. An experiment was conducted in which 10 domain experts at different command levels were asked to help the users decide about which weapon to deploy over a specific terrain in the war situation. This dataset contained the details of 4 terrains, 5 weapon categories, 30 weapons under each weapon category, and 6 weapon attributes.

4.1 Setup

The ITMTC system starts with 10 recommender agents (domain experts), who have their own knowledge about the weapons in specific terrain stored in their own location. User agent creates when user logs into the system. The user agent has a certain degree of trust on these recommender agents, which is represented in the Table 1. In Table 2, degrees of significance, that the user agent associates with the attributes of a weapon, are shown. The Table 3 gives the preference list that the user agent gives to the recommender agents. The information shown in Table 4 is collected by recommender agents during the unintentional encounters with user agent A.

User agent receives the query regarding weapon recommendation from the user and passes this query to its trustworthy recommender agents. The recommender agents respond with the degrees of membership and non-membership about the weapons, as shown in Table 5. Finally Table 6 shows the aggregated list of all the recommendations as computed by the user agent and given to the user.

The degree of importance is negative for those weapons that do not conform to the taste of the user but have been suggested as these have mass appeal.

5. CONCLUSIONS

Committing weapons to a given terrain is a part of a larger problem known as the weapon-target assignment (WTA) problem that has received a great deal of attention in recent years by the strategic community. Recommender system presented in this paper with case studies on the influence of terrains on modern tactical combat is a step forward in this direction. Using the developed prototype for the recommender system, a user can get the recommendations on the use of weapon / set of weapons in a user specified terrain type from the available set

Table 1. The degree of trust on the recommender agents according to the user agent A

Recommenders	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
Degree of trust	0.78	0.68	0.85	0.23	0.76	0.33	0.87	0.68	0.77	0.93

Table 2. Degree of significance of attributes of weapons

Weight	Armour	Power/weight	Max. Range	Elevation	Manoeuvrability
0.7845	0.6873	0.5974	0.2345	0.2323	0.3728

Table 3. Preference list about taste of user maintained by recommender agents preferences in the sublists (P_A)

Weight	Arjun MBT	Bofors 37 MM	ASU-85	BM-30	T-72
Armour	ASU-85	BM-30	Bofors 37 MM	Arjun MBT	T-72
Power/Weight	BM-30	T-72	Bofors 37 MM	ASU-85	Arjun MBT
Max. Range	ASU-85	Arjun MBT	BM-30	T-72	Bofors 37 MM
Elevation	BM-30	Bofors 37 MM	Arjun MBT	ASU-85	T-72
Manoeuvrability	Arjun MBT	BM-30	T-72	ASU-85	Bofors 37 MM

Table 4. Uncertain list (U_A) about taste of user maintained by recommender agents

Uncertain list (U_A)				
BMP-1	Pinaka multi barral	3 inch GUN M3	Royal ordanance L-7	BM-21

Table 5. Recommendations of the five recommender agents

Weapons Recommended \ Recommender		R_1	R_2	R_3	R_4	R_5
ARJUN MBT	μ	0	0.91267			
	ν	0.1732	0.08733			
BOFORS 37 MM	μ		0			0.790012
	ν		0.2332			0.209982
3 IN GUN 75	μ	0.23562		0.12461		
	ν	0.76438		0.87539		
ASU-85	μ		0.83391		0.92146	
	ν		0.16609		0.07854	
BM-21	μ		0.1179		0.0059	0.01443
	ν		0.8821		0.9941	0.98557
BMP-1	μ	0.65			0.46	
	ν	0.35			0.54	
PINAKA MULTI BARREL	μ		0.12543		0.48779	
	ν		0.87457		0.51221	
T-72	μ	0	0	0		
	ν	0.89	0.63	0.63		
BM-30	μ	0.77678		0		0
	ν	0.22322		0.2		0.1
ROYAL ORDANANCE L7	μ				0.9181	0.9072
	ν				0.0819	0.0928

Table 6. The aggregated list as obtained by the user agent A

Weapons	Degree of importance
ASU-85	0.509504
Royal Ordanance L7	0.399057
Arjun MBT	0.377892
BM-30	0.255053
Pinaka Multi Barrel	0.229445
Bofors 37 MM	0.137794
BMP-1	0.094576
3 inch Gun 75	0.006438
T-72 Tank	–0.08492
BM-21	–0.006628

of weapons. The prototype combines several domain experts' knowledge about terrain over which forces and weapon systems operate to compute recommendations, thereby expanding the body of knowledge regarding the effects of terrain upon modern tactical combat. Recommendations are generated in the form of IFS having membership, non-membership and hesitation part. The concept of trust has been incorporated in the paper to match the human thinking process. Trust is also updated by the user on recommender based on the recommendation received. The prototype system is implemented using JADE (Java Agent Development Environment), JSP and Oracle 10g on windows environment.

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