Fusion of Expert Information in Content-Based Multimedia Retrieval with Group Decision Support

Andrzej M.J. Skulimowski [0000-0003-0646-2858] 1,2
[1] AGH University of Science and Technology, Chair of Automatic Control and Robotics, Decision Science Laboratory, Mickiewicza ave. 30, 30-059 Kraków, Poland
[2] International Centre for Decision Sciences and Forecasting, Progress & Business Foundation, J. Lea street 12B, 30-048 Kraków, Poland
ams@agh.edu.pl

Abstract. This paper proposes a new approach to fuse recommendations of experts involved in multicriteria decision support procedures. Recommendations are formulated by experts independently as elements of four predefined reference sets. The decision situation corresponds either to the scheme 'one decision maker – multiple recommending experts' (group decision support) or 'multiple decision makers – multiple experts' (group decision making and support). We define the internal, mutual, and plausibility inconsistencies and propose a procedure to verify consistency, regularize the reference values, and fuse them. An expert's trust coefficient decrease when a reference value recommended by this expert is modified during the regularization process. Thus, the regularization outcomes can be assessed ex ante with respect to the total losses of experts' credibility and to the quality of the resulting reference set. The decision process will be illustrated by an example of content-based multimedia retrieval from the AI-based knowledge repository developed within a recent research project.

Keywords: Multicriteria decision making, Content-based information retrieval, Reference set method, Multiple reference points, Group decision support

1 Introduction

In this article we consider the situation, where multiple experts involved in decision support provide independent hints to one or more decision makers. These seek a best compromise selection of multimedia learning material to be retrieved from an AI-based learning platform (AILP). Experts' recommendations are formulated as reference points of different kind. By definition, the reference points are distinguished elements of the criteria space $E:=\mathbf{R}^N$, which are assigned a special meaning to one or more decision maker(s) in the multicriteria optimization problem

$$[F:=(F_1,\ldots,F_N):U\to E]\to min(\theta), \tag{1}$$

where θ is an ordering cone in E. So defined reference points can be used as additional preference information in the extended Topsis [2], bipolar [7], reference set (RefSet, [4]), or safety principle method. The multicriteria decision making (MCDM) methods based on reference points have been widely used to solve real-life compromise decision selection in problem (1) such as industrial design, staff recruitment, autonomous decision modeling or preference-based filtering in content based image retrieval (CBIR, [3],[6]). The latter area constitutes the background for content-based multimedia retrieval from the knowledge repository [8], where our approach is dedicated to.

The expert decision recommendation procedure with multiple reference points consists in defining several – usually three or more - classes of reference points, while the elements of each class are assumed to be characterized by the same utility value. Below we recall the definitions of four basic classes of reference points [4] and link them to the multimedia retrieval problem:

A_0 - *Bounds of optimality* - the values of A_0 correspond to the alternatives with properties that exceed actual needs, such as too advanced or too extensive courses.

A_1 - *Target points* - the elements of the criteria space that model ideal but usually non-admissible solutions. If none of them can be selected, the decision-maker should try to choose the learning material with parameters as close as possible to the coordinates of any of elements of A_1. These points are also termed ideal aspiration levels.

A_2 - *Status-quo solutions* - attainable criteria values which should be outperformed during the decision-making process, such as parameters of the multimedia learning material already available at the pre-decision stage without further search in the AILP.

A_3 - *Anti-ideal reference points* - express the wrong choice, for example failed learning material selection in the past. Therefore, the set A_3 should be avoided during the decision-making by choosing a solution most distant to decisions represented by A_3.

Reference points can be used to estimate an underlying utility (or value) function v according to the assumption that the elements of A_i are assigned the same deterministic utility value $v(A_i)=\alpha_i>0$ such that $\alpha_i<\alpha_j$ when $j<i$. So, v is to be maximized on U as a scoring function for the problem (1). The background of the multiple reference points (MREF) and reference set methods (RefSet) has been given in [1] and [4], while their extensions related to the CBIR problem are provided in [3] and [6]. In these decision support approaches, neighboring classes of reference points are pairwise aggregated to form ,two subsets of the criteria space, one to be approached and the other to be avoided. This paper is devoted to the study of reference points consistency. We provide the rules and operations to convert inconsistent sets of reference points into the structure that complies with the utility modelling principles and to fuse them.

2 The Consistency of Expert Recommendations

The utility function estimation from expert judgments requires consistency in assigning utility values to reference points. These must comply with the monotonicity of the utility function v. Furthermore, their situation with respect to the attainable set $F(U)$ in E must conform to the common-sense meaning of reference points presented in the previous section. This additional property will be termed here consistency with the problem (1). The multiple reference points approach presumes that all elements of the class A_i correspond to the same value of the estimated utility function. We will call this property *internal consistency* of the class A_i.

Definition 1. *The set of reference points A_i is internally consistent iff*

$$\forall q_1, q_2 \in A_i : q_1 \text{ and } q_2 \text{ are noncomparable with respect to } \theta. \tag{2}$$

Moreover, each one of the sets A_i, $0 \le i \le K$, where K+1 is the number of classes of reference points, should be well-defined with respect to all other sets of reference points. This requirement will be formulated as an assumption that each element of A_j should be dominated by an element of A_{j+1}, for $0 \le j \le K-1$, i.e.

$$\forall x \in A_j \ \exists y \in A_{j+1} : \ x \le_\theta y. \tag{3}$$

To obtain the desired properties of the level sets of v we impose an additional condition (4), symmetric to (3), which allowed us [4] to define the *mutual consistency*,

$$\forall x \in A_{j+1} \ \exists y \in A_j : x \le_\theta y. \tag{4}$$

Definition 2. *The reference classes A_j and A_{j+1} that satisfy the conditions (3)-(4) will be termed mutually consistent.* ■

Along with consistency, rationality is a fundamental property of multicriteria decision-making methods that should be verified in the first order of importance.

Definition 3. *A multicriteria decision making procedure is termed rational if its ultimate solution is nondominated with resppect to the order defined in* (1). ■

Due to frequent occurrence of inconsistent hints, specifically in the context of of multimedia learning material selection, checking and correcting mutual consistency turned out to be an essential part of recommendation-based decision-making processes involving the AILP users [5],[8]. This is justified by the following fact:

Theorem 1. *If all reference classes A_i for the problem (1) are both internally and mutually consistent, then the solution process described as RefSet in* [4] *is rational.* ■

After estimating the attainable set $F(U)$ in (1) it may happen that the actual situation of reference points differs from that required by Defs. 1-3 above. Then, it is necessary to re-formulate experts' judgments according to the general rule that the rationality of the compromise solution is superior to the intuitive interpretation of reference points. This is the aim of the regularization procedure that uses a.o. reference point averaging, re-defining, splitting and merging the reference classes. In the next section, this procedure is illustrated with an example referring to multimedia course selection.

3 An Example of Content-Based Multimedia Course Selection

As an application example of our approach, we present a procedure of recommending videos, massive online courses (MOOCs), and other multimedia courses to the users of the AILP developed within the recent Horizon 2020 research project [8]. Instructors are principal recommending experts, while students are the decision makers who select the learning material according to the criteria G related to the achievement of learning goals, learning efficiency and comfort. Usually, the criteria G are expressed as preference-preserving functions of certain machine-measurable pre-criteria F.

Example 1. Assume that two instructors I_1 and I_2 with the same trust coefficients 0.8 recommend multimedia courses according to the qualitative criteria $G=(G_1,G_2)$, where G_1 describes the correctness and clarity of presentation, G_2 - the presence of specific adequate real-life cases. According to (1), G is to be minimized, which means that its numerical values should be interpreted as deviations from a certain ideal course. There are three directly measurable criteria $F=(F_1,F_2,F_3)$, with F_1 - the coverage of the obligatory and auxiliary stuff (in %), to be determined by text mining from the course annotations, F_2 – the average quality of graphics and videos – to be determined by checking the resolution and provenience of images and videos, and F_3 is the availability of supplementary material normalized on the scale [0,1]. The dependence of G on F is disclosed initially in an explicit form for the sets A_i only. However, it can be learned with adaptive regression techniques from earlier recommendation-selection processes that involved other experts and users, i.e. G is represented as $G=\varphi\circ F$. Current recommendations update the hitherto determined coefficients of φ. The learning goals can be made explicit as a query that defines a preliminary selection of the learning content to be considered in further recommendation and multimedia selection process. Consequently, this query corresponds to the constraints U that in this example consist of three nondominated courses such that $G(F((U))=\{(2,4),(3,3),(4,2)\}$. The reference points from A_1 and A_2 are provided in Table 1 as vectors with the corresponding values of G and F. Additionally, we assume that $A_0=\{(0,0)\}$ and $A_3=\{(8,4),(7,7)\}$.

Table 1. The reference points defined by experts within the course selection process.

A	Expert	G_1	G_2	F_1	F_2	F_3
$a_{1,1}$	I_1	2	1	1	0.8	0.9
$a_{1,2}$	I_2	1	3	1	0.9	0.7
$a_{2,1}$	I_1	7	3	0.8	0.6	0.6
$a_{2,2}$	I_2	5	6	0.7	0.7	0.7
$a_{2,3}$	I_2	4	7	0.6	0.7	0.9
$a_{2,4}$	I_2	6	7	0.6	0.5	0.7

After the expert recommendations are entered to the decision support system, their verification, fusion, and decision selection process runs as follows:

1. The *verification* of the conditions (2)-(4) discovers an internal inconsistency in the class A_2 while all other classes and their mutual situation are correct.
2. The *regularization* procedure starting from $a_{2,1}$ and $a_{2,4}$ replaces this pair with their average $a_{2,5}$=(5;7). This new reference point turns out to be still comparable with $a_{2,2}$, so in the second step of this run both are replaced with $a_{2,6}$=(5;6.5) that - together with $a_{2,1}$ yields a correct class A_2. The next run of averaging takes into account the second potential expert recommendation fusion, where $a_{2,2}$ and $a_{2,4}$ are compared first, so that a different average is calculated, namely $a_{2,8}$=(5.5;6.5) that is noncomparable with $a_{2,1}$. Both runs yield correct classes A_2, so to calculate the utility function, the procedure averages all runs and retains the final class A_2'={(6;2),(5.25;6.5)}. The trust coefficients of I_1 and I_2 are decreased proportionally to the distances between the final averaged point and the replaced values.

3. The *recommendation fusion* procedure extrapolates the utility v of criteria G values from the level sets constructed as triagulations of reference points of each class; then the utility $\tilde{v}$, a function of decisions u, is expressed as $\tilde{v}=v^\circ\varphi^\circ F$.
4. The function φ is updated based on G and the new set A_2 wihin an unsupervised learning procedure and applied to find the course u_1 with the highest utility v. The course u_1 such that $G(F(u_1))=(2,4)$ maximizes v and is presented to the user.
5. The overall procedure stops when the proposed course is accepted, otherwise the above steps 1-4 are repeated with new expert recommendations and/or user-defined course parameters included into the classes A_i, for i=0,1,2,3. ■

Let us observe that all elements of reference classes are non-comparable with respect to F, although the regularization procedure was necessary when considering the criteria G. This explains the source of potential inconsistencies of expert judgments, who analyze the course features F, but present user-oriented assessments in terms of G.

The criteria of individual learners f may be different from G and not disclosed to instructors. They can serve as user preferences when selecting compromise courses.

4 Conclusions

The output of the above-presented decision making process may depend on the order the reference points and classes are taken into account. This is why the results can be averaged by performing the regularization for every permutation of points in each class. It can be shown that only permutation inside classes are relevant. If the number of recommending instructors is smaller than ten, and each of them defines no more than ten reference multimedia items, the above averaging is computationally feasible.

References

1. Górecki, H.; Skulimowski, A.M.J.: A Joint Consideration of Multiple Reference Points in Multicriteria Decision Making. *Found. Control Engrg.*, 11(2), 81-94 (1986).
2. Lai, Y.-J.; Liu T.-Y.; Hwang. C.-L.: TOPSIS and MODM. *EJOR*, 76, 486-500 (1995).
3. Rotter, P., Skulimowski, A.M.J.: Preference extraction in image retrieval. In: Ma, Z. (Ed.). *AI for Maximizing Content-based Image Retrieval*, IGI, Hershey, pp. 237-262 (2009).
4. Skulimowski, A.M.J.: Methods of Multicriteria Decision Support Based on Reference Sets. In: Caballero R., et al. (eds.) Advances in Multiple Objective and Goal Programming, *Lect. Notes in Econ. and Math. Syst.*, 455, Springer, pp. 282-290 (1997).
5. Skulimowski, A.M.J.: Cognitive content recommendation in digital knowledge repositories – a survey of recent trends. In: Rutkowski, L. et al. (eds.), 16th ICAISC, Proceedings, *Lect. Notes in Artif. Intell.*, 10246, 574–588 (2017), doi: 10.1007/978-3-319-59060-8_52.
6. Skulimowski, A.M.J., Rotter, P.: Applying reference sets in content-based interactive image retrieval. *Multiple Criteria Decision Making*, 4(SI, Trzaskalik, T., ed.), 185-202 (2009).
7. Trzaskalik, T.: Bipolar sorting and ranking of multistage alternatives. *Central Eur. J. Oper. Res.*, 29, 933–955 (2021), https://doi.org/10.1007/s10100-020-00733-2.
8. Vagliano, I., et al.: Open Innovation in the Big Data Era with the MOVING Platform, *IEEE MultiMedia*, 25(3), 8–21 (2018), https://doi.org/10.1109/MMUL.2018.2873495.