Action Sequence Matching of Team Managers

Olaf Flak[1], Cong Yang[2] and Marcin Grzegorzek[3]
[1]*Faculty of Radio and Television, University of Silesia in Katowice, Katowice, Poland*
[2]*Pattern Recognition Group, University of Siegen, Siegen, Germany*
[3]*Faculty of Informatics and Communication, University of Economics in Katowice, Katowice, Poland*
cong.yang@uni-siegen.de

Keywords: Team Managers, Partial Matching, Action Matching.

Abstract: Traditionally, team managers are analysed and compared based on human perception with data collected from surveys and questionnaires. These methods normally have low efficiency especially in dynamic and complex environments. In order to improve the accuracy and stability of manager analysis in management science, in this paper, we propose a novel manager representation method which is general and flexible enough to cover most types of managers. For manager analysis, we introduce the first manager matching algorithm that calculates the global similarity between managers. The proposed matching algorithm not only returns robust and stable manager similarities, but also details the matched parts among managerial action sequences. With this, the proposed methods provide more research possibilities in management science.

1 INTRODUCTION

A team is defined as a social system of two or more units that are embedded in an organisation (Hoegl and Parboteeah, 2007). In a team, team members perceive themselves and each other as collaborating on a common task. For the purpose of improving the team work ability on more dynamic and complex environments (Mathieu et al., 2008) today, research on team work becomes more and more relevant (Shakshuki et al., 2003) and has attracted a lot of attention in the past decades (Mathieu et al., 2008). One common perception of those researches is that team managers are the spirit of team works (Sohmen, 2013). A team manager can be defined as a team member (1) who comprises influencing actions affecting the other team members and (2) who chooses objectives for the team, organizes activities to accomplish the objectives and (3) who motivates team members to achieve the objectives and maintains cooperative relationships and teamwork to optimise collective time of work (Perlow, 2014).

A team and a team manager are the warp and woof of the dynamic fabric of organisations. They cannot exist without each other activated by managerial actions as a constellation of specific objectives, resources and processes (Sohmen, 2013). Moreover, in order to ensure a team can achieve the established goals with clear assumptions, it is crucial to clarify managerial actions that govern team actions (Sinar and Paese, 2016). Consequently, it leads to a strong need for research on managerial action analysis (Halliday and Stacey, 2009). In general, there are two research challenges related to managerial action analysis. The first challenge is how to model the managerial actions in order to fully represent the characteristics of a team manager. The second challenge is what kind of methods could be employed to distinguish team managers and, additionally, to label their styles of leadership. Traditionally, the first challenge is addressed by the action sequence analysis which used to track the order of actions over time (Abbott, 1990). Those actions are usually declared by managers and then collected by questionnaires (Barnes, 1980). Based on that, a team manager can be represented by a data map describing the action features of, e.g. "what", "when" and "how" (Beshears and Gino, 2015). However, this method is not robust because some managerial actions could be ignored due to the poor memory and impression of team managers (Flak and Pyszka, 2013). Moreover, this representation method is not general and has low flexibility since different managers may take different types of managerial actions (Beshears and Gino, 2015).

In order to solve these problems, in this paper, we propose a general model to represent a manager by managerial actions and their features. Specifically, a manager is first represented by an action se-

Flak, O., Yang, C. and Grzegorzek, M.
Action Sequence Matching of Team Managers.
DOI: 10.5220/0006189203860393
In *Proceedings of the 6th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2017)*, pages 386-393
ISBN: 978-989-758-222-6

quence. After that, each action is modelled by action features within different feature groups. Theoretically, the proposed method can preserve both fine- and coarse-grained information of a manager. The main reason is that we describe each managerial action by several different action features. Moreover, the proposed method is general enough to cover most types of managers since the each managerial action is represented by flexible feature groups. Lastly, the proposed model can be easily adapted to different online/off-line managerial tools.

For the second challenge, the team managers are normally distinguished and labelled by human perception (Whetten and Cameron, 2016) of, e.g. managerial actions, attitudes and values. However, there are four main disadvantages of such a method: Firstly, it cannot accurately measure the similarity/dissimilarity between managers since human perception is highly abstract. Secondly, this method is not robust due to the instability of human perception (Yang et al., 2016). Thirdly, this method has low efficiency since the distinguishing and labelling processes are both applied manually. Lastly, even if two managers are similar to each other by human perception, it is hard to point the detailed similar/dissimilar parts among their managerial action sequences. Therefore, we propose a method that can overcome these disadvantages. Particularly, by the action matching between managers, the proposed method not only returns the similar parts among action sequences, but also calculates the global similarities. In order to do so, the proposed matching method integrates both local and global matching strategies. The local matching strategy allows an accurate measuring of local similarity between action blocks within action sequences while the global matching strategy calculates the overall similarity between managers based on the local similarities. In such a case, the proposed method can automatically and accurately distinguish team managers. In addition, this method provides more research possibilities in management science (Siedlok and Hibbert, 2014).

The main scientific contributions of this article include: (1) We apply an interdisciplinary research between management science and pattern recognition to deal with the team manager representation and matching. (2) We introduce an effective and general team manager representation method. (3) We propose the first algorithm that can accurately measure the similarity between team managers.

2 RELATED WORK

The view of a manager has changed many times over the last hundred years. At the beginning of the scientific management age, a manager in an organisation was represented by his/her functions, such as a reflective planner, an organiser, a leader or a controller (Brodie, 2007). However, these approaches do not have the information of real managerial actions. Besides many other later approaches, it took 50 years to experience a significant change in the view of manager natures. Particularly, the most dominating approaches consist of two main concepts: (1) *managerial roles* that a manager should play (Mintzberg, 1973), and (2) *managerial skills* that a manager should have (Beaudry and Francois, 2010). Koontz and O'Donneil launched a discussion on the meaning of managerial skills in 1964 (Koontz and O'Donneil, 1964). In 1974 Katz proposed an approach in which a manager is represented by managerial skills. He claimed that successful managers are indeed eclectic and they must possess and be skilled in technical, human and conceptual areas of organisational life (Katz, 1974). In 1973 Mintzberg concluded that a manager can be described in terms of 10 roles (Mintzberg, 1973). Due to the deep influence of these concepts among scientists and practitioners, in most publications a manager is represented by managerial skills and managerial roles (Sinar and Paese, 2016).

Based on the survey and analysis of the published methods, we draw a conclusion that managerial skills and managerial roles as traditional theoretical concepts are sufficient to represent a team manager. But they are still not general and robust enough to describe most types of managers. The main reason is that the concepts of managerial skills and managerial roles only illustrate what competences a manager should have and should do, respectively. They do not show what a manager really does. Built on this observation, in Section 3, we represent a manager by managerial actions which are the missing point in relations between managerial skills and managerial roles. With this, the proposed representation method integrates managerial skills and managerial roles and turns them into managerial actions. Therefore, comparing to the traditional manager representation method, the proposed approach has high distinguish powering and stability. In addition, this representation method is suitable for action sequence matching in Section 4.

Moreover, we also observe that most research projects were conducted by the survey method with questionnaires as a research tool (Sinar and Paese, 2016). With this method, it is hard to quantitatively compare the difference between managers. In order to distinguish different types of managers, the traditional perception-based methods are not robust since human perception could be influenced by many fac-

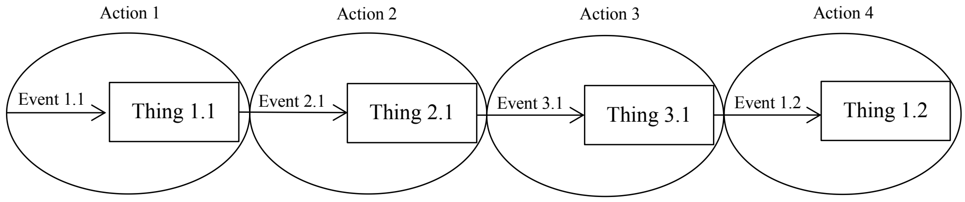

Figure 1: Fundamental structure of actions.

tors such as memory, emotions, etc. These methods are time-consuming because they are normally carried out manually (Alexandru and Diana, 2015) or semi-automatically (Sinar and Paese, 2016). To solve these problems, we propose an automatic method that can calculate the similarity between managers based on their action sequences. In addition, the partial similar/dissimilar action blocks within sequences can also be returned. With the proposed method, researchers can apply a deeper and more accurate analysis of managers and their actions. In such a case, the proposed method gives more potential research possibilities in management science. Moreover, since the proposed manager representation and matching are fully automatic methods, they can be adopted to some management applications (Mithas et al., 2005). For instance, a manager can be guided by action sequence matching with the knowledge action sequences from other managers.

3 MANAGER REPRESENTATION

In this section we first introduce the relationship between managers and their actions. After that, we theoretically describe the feasibility of manager representation using actions and their features. Built on this, a mathematical model for manager representation is proposed.

3.1 Managers and Actions

In this article, a team manager is denoted as Ω. As discussed in Section 1 and 2, compared to the traditional approaches that represent Ω by managerial roles and managerial skills, we propose to represent Ω by managerial actions. The rationale behind this is that a managerial action can be defined as a real activity which a manager does in order to play a managerial role and have a certain managerial skill (Pavett and Lau, 1982). In such a case, a managerial action is the connection between a managerial role and a managerial skill. Consequently, the proposed representation method has higher description power.

To represent each managerial action, it is important to discuss and analyse its ontological concept: The system of organisational terms (SOT). SOT is an original theoretical construct in which the organisation performance is tracked and recorded. In order to do so, observation techniques are used along with the on-line management tools (Flak, 2015). The philosophical foundation of SOT is based on Wittgenstein's philosophy: Facts (the only beings in the world) and their "states of facts" (Brink and Rewitzky, 2002). We extend this concept and propose that managerial actions can be organised by events and things. Specifically, as shown in Figure 1, each event and thing have the label $I.J$, in which I and J represent a number and a version of a thing, respectively. Event 1.1 causes thing 1.1, which in turn releases event 2.1 that creates thing 2.1. Thing 2.1 starts event 3.1 which creates thing 3.1. Then, thing 3.1 generates a new version of the first event, i.e. event 1.2. In such a way, a new version of the first thing is created, which is called thing 1.2.

According to events and things, a managerial action can be represented by time domain features and content domain features, respectively (Brinkerhoff, 1985). In this article, we employ the time domain features since such features can be easily captured and quantised. In contrast, the content domain features involve words, sentences, expressions, characters and figures, etc. which are hard to be quantised by existing models (Alnajjar and Flak, 2016).

3.2 Representation Model

As a manager is organised by several actions, we represent it by features of each action. Specifically, as shown in Figure 2, a manager Ω is composed by M actions:

$$\Omega = \{\boldsymbol{a}_1, \cdots, \boldsymbol{a}_M\} \quad . \tag{1}$$

For a single action $\boldsymbol{a}_i$, it can be represented by a T-dimensional feature vector:

$$\boldsymbol{a}_i = [f_{i1}, \cdots, f_{iT}]^{\mathsf{T}} \quad . \tag{2}$$

where f denotes a single feature value, $i = 1, 2, \cdots, M$. As discussed in Section 3.1, those features can also be classified into H groups based on their characteristics, $H \leqslant T$. Moreover, the feature

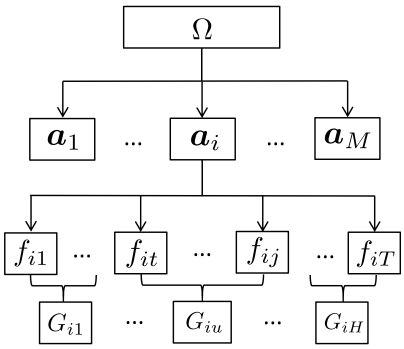

Figure 2: The proposed model to represent a manager Ω.

number in a group G_{iu} may be different from others, $u = 1, \cdots, H$. For example, in Figure 2, G_{i1} and G_{iH} could have different feature numbers. For notational simplicity we assume that the features of $\boldsymbol{a}_i$ are ordered according to the order of their groups. In such a case, $G_{im} = [f_{it}, \cdots, f_{ij}]$, $1 \leqslant t \leqslant j$ and $t \leqslant j \leqslant T$. Consequently, an action $\boldsymbol{a}_i$ can also be represented by feature groups:

$$\boldsymbol{a}_i = \{G_{i1}, \cdots, G_{iH}\} \quad . \tag{3}$$

Considering all M actions of a manager Ω, it can be represented by all action features within H feature groups:

$$\Omega = \{\boldsymbol{G}_1, \cdots, \boldsymbol{G}_u, \cdots, \boldsymbol{G}_H\} \quad . \tag{4}$$

where $\boldsymbol{G}_u$ is a $M \times (j - t + 1)$ matrix in which all M action features within a feature group $[f_t, f_j]$ are preserved. The proposed representation method in Eq. 4 will be used for action sequence matching in Section 4.

It should be noted that the idea of representing a manager by feature vectors is not new. Such an idea is also similar to one of the first research by F. and L. Gilbreth in the field of scientific management at the beginning of 20th century (Karsten, 1996). They investigated human motions at work, which was the beginning of workforce automation in industries (Spriegel et al., 1953). Moreover, in literature we can find other representation approaches used in production (Al-Saleh, 2011), healthcare services (Lopetegui et al., 2014), process of physical workers (Magu et al., 2015), and to some extent, in managerial work (Tengblad, 2002). However, different from these approaches, our method is more flexible to be adapted in different scenarios. In addition, the proposed representation model in Figure 2 is suitable to use in action sequence matching in Section 4.

4 MANAGER MATCHING

In this section, we propose an efficient matching algorithm to find partially similar parts among action sequences from different team managers. Moreover, it is important to provide a reasonable similarity measure for tasks such as manager comparison and retrieval, etc. Therefore, a manager similarity method is introduced in the second part of this section.

4.1 Partial Matching

In order to find a partial match between two given managers Ω_1 and Ω_2, their corresponding action sequences S_1 and S_2 are compared. As introduced in Section 3.2, each action $\boldsymbol{a}$ is described by a T-dimensional feature vector. Therefore, the action sequences S_1 and S_2 can be represented by feature matrices with size $M \times T$ and $N \times T$, respectively. M and N are the number of actions. For notational simplicity we assume that $M \leqslant N$.

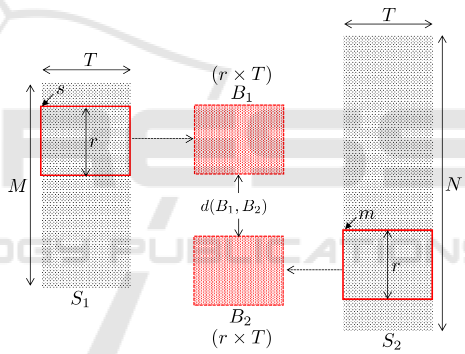

Figure 3: An illustration of the general idea of partial matching. B_1 and B_2 are two $r \times T$ sized action blocks selected from the action sequences S_1 and S_2, respectively. $D(s, m, r)$ denotes the dissimilarity between B_1 and B_2.

The aim of manager matching is to identify parts of the two action sequences that are similar to each other. In terms of comparing the two descriptor matrices, as shown in Figure 3, it equals to find $r \times T$ sized feature blocks B_1 and B_2, starting at the action $\boldsymbol{a}_{1s}$ in S_1 and $\boldsymbol{a}_{2m}$ in S_2 which yield a small dissimilarity value $d(B_1, B_2)$. r is the number of actions in the matching blocks B_1 and B_2. s and m denote the index of start actions in S_1 and S_2, respectively. As illustrated in Eq. 4, each manager Ω can be represented by H feature groups. Since B_1 and B_2 have the same dimensional features and feature groups as Ω, they can also be represented by:

$$\begin{aligned} B_1 &= \{\boldsymbol{G}'_{11}, \cdots, \boldsymbol{G}'_{1u}, \cdots, \boldsymbol{G}'_{1H}\} \\ B_2 &= \{\boldsymbol{G}'_{21}, \cdots, \boldsymbol{G}'_{2u}, \cdots, \boldsymbol{G}'_{2H}\} \end{aligned} \tag{5}$$

where $\boldsymbol{G}'_{1u}$ and $\boldsymbol{G}'_{2u}$ are the $r \times (j-t+1)$ feature group matrices, $u = 1, \cdots, H$. This is because a feature group $\boldsymbol{G}'$ contains r number of actions. Moreover, as shown in Eq. 4 and Figure 2, the feature number in a feature group is indicated by $(j-t+1)$.

Based on Eq. 5, in this article, $d(B_1, B_2)$ is calculated by the integrated Bhattacharyya distance (Dubuisson, 2010) from H feature groups:

$$d(B_1, B_2) = \frac{1}{H} \sum_{u=1}^{H} \tau_u D_B(\boldsymbol{G}'_{1u}, \boldsymbol{G}'_{2u}) \tag{6}$$

where τ is the weight for fusing H feature groups and $D_B(\boldsymbol{G}'_{1u}, \boldsymbol{G}'_{2u})$ denotes the Bhattacharyya distance between two feature groups. In practice, τ can be searched using the heuristic method of Gradient Hill Climbing integrated with Simulated Annealing (Yang et al., 2015). Otherwise, it can be set to one for all feature groups. Specifically, the Gradient Hill Climbing (Russell and Norvig, 2009) method starts with randomly selected parameters. Then it changes single parameters iteratively to find a better set of parameters. A fitness function then evaluates whether the new set of parameters performs better or worse. The Simulated Annealing strategy (Kirkpatrick et al., 1983) impacts the degree of the changes. In later iterations, the changes to the parameters are becoming smaller. Consequently, with a small part of testing data in the preliminary experiments, $\tau_1, \cdots, \tau_H$ can be properly assigned.

Furthermore, the Bhattacharyya distance $D_B(\boldsymbol{G}'_{1u}, \boldsymbol{G}'_{2u})$ is calculated by:

$$D_B(\boldsymbol{G}'_{1u}, \boldsymbol{G}'_{2u}) = \frac{1}{4} \ln\left(\frac{1}{4}\left(\frac{\sigma^2_{1u}}{\sigma^2_{2u}} + \frac{\sigma^2_{2u}}{\sigma^2_{1u}} + 2\right)\right) + \frac{1}{4}\left(\frac{(\mu_{1u} - \mu_{2u})^2}{\sigma^2_{1u} + \sigma^2_{2u}}\right) \tag{7}$$

where σ and μ are the variance and mean of a features within a group $\boldsymbol{G}'$, respectively. With Eq. 7, the Bhattacharyya distance among all feature groups can be calculated and then the global dissimilarity $d(B_1, B_2)$ between two feature blocks B_1 and B_2 is generated using Eq. 6.

As introduced above, $d(B_1, B_2)$ is built on the combination $\{s, m, r\}$: Start action in S_1 (that is s), start action in S_2 (that is m) and action number in a matching block B (that is r). Therefore, to find similar blocks among S_1 and S_2 all different matching possibilities and chain lengths r have to be considered and the brute-force method (Bellman, 1954) becomes inefficient for larger number of actions. Therefore, different authors as e.g. (Osada et al., 2002) proposed approximations where for example only every n-th action is considered as the starting action.

Inspired by (Donoser et al., 2009), we propose an algorithmic optimisation to overcome the limitations of the brute-force approach (Osada et al., 2002). The proposed method is based on a modified Summed-Area-Table (SAT) approach (Hensley et al., 2005) to calculate all the dissimilarity values $d(B_1, B_2)$ among different combinations of $\{s, m, r\}$. The SAT concept was originally proposed for texture mapping (Crow, 1984) and then brought back to the community of computer vision by Viola et al. (Viola and Jones, 2001) as integral image. The integral image concept allows to calculate rectangle image features like the sum of all pixel values for any scale and any location in constant time (Donoser et al., 2009). However, different from the method (Donoser et al., 2009) in which N integral images are generated for triples $\{s, m, r\}$ searching, the proposed method only uses M integral images to speed up the matching process.

Particularly, in order to calculate the dissimilarity value $d(B_1, B_2)$ for all possible configuration triplets $\{s, m, r\}$ in the most efficient way, M integral images $Int^1, \cdots, Int^r, \cdots, Int^M$ are built based on Eq. 6 for the block length r from 1 to M. In such a case, each integral image Int^r is the $(M-r) \times (N-r)$ matrix. The main reason is that we need to consider all possible matches from action blocks in S_1 and action blocks in S_2. Based on these M integral images the dissimilarity values $d(B_1, B_2)$ can be calculated for every block of any length starting at any action in constant time.

Finally, all matching triples $\{s, m, r\}$ which provide a dissimilarity value $d(B_1, B_2)$ below a fixed threshold are returned as the final matched parts among two action sequences S_1 and S_2. As discussed in (Donoser et al., 2009), the detected matches may overlap. Therefore, the final result is obtained by merging the different returned matches.

4.2 Manager Similarity

To calculate the global similarity between two managers Ω_1 and Ω_2, a combination of descriptor difference (Yang et al., 2014) and the bending energy of an estimated transformation (Torsello and Hancock, 2004) is commonly used. However, these methods normally only focus on the coarse-grained differences among action sequences S_1 and S_2 and the property of fine-grained similar and dissimilar blocks are not fully used. Moreover, in Section 4.1 we already collect the partial dissimilarities with all possible block lengths. With this in mind, we adapt a measure described by Bronstein et al. (Bronstein et al., 2009) and Donoser et al. (Donoser et al., 2009) to calculate the global similarity between managers.

Specifically, we use a Pareto-framework for quantitative interpretation of partial similarity. In order to do so, two quantities are defined: partiality $\lambda(B_1, B_2)$, which describes the block lengths (the higher the value, the smaller the part) and dissimilarity $d(B_1, B_2)$, which measures the dissimilarity between the blocks, where B_1 and B_2 are two action sequence blocks. In this paper, partiality $\lambda(B_1, B_2)$ is calculated by $1/r$, where r is the block length (Section 4.1). Here we describe a pair of partiality and dissimilarity values $(\lambda(B_1, B_2), d(B_1, B_2))$ as Pareto optimum $\Phi(B_1, B_2)$ (Donoser et al., 2009), that is $\Phi(B_1, B_2) = (\lambda(B_1, B_2), d(B_1, B_2))$. With $\Phi(B_1, B_2)$, it is possible for us to observe the lowest dissimilarity for the given partiality. As described in Section 4.1, the proposed partial matching algorithm automatically evaluates all possible matches for all possible block lengths, we can easily collect all Pareto optimums $\Phi(B_1, B_2)$ by focusing on the minimum dissimilarity values in M integral images.

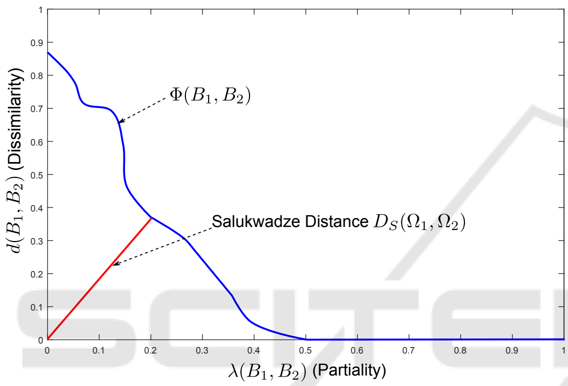

Figure 4: The proposed approach for calculating similarity between managers using the Salukwadze distance.

Finally, to get the global similarity $D_S(\Omega_1, \Omega_2)$ between mangers Ω_1 and Ω_2, as shown in Figure 4, all Pareto optimums are visualised as a curve, referred to as the set-valued Pareto frontier and the so-called Salukwadze distance (Bronstein et al., 2009) is employed based on the collected Pareto frontier by

$$D_S(\Omega_1, \Omega_2) = \inf_{B_1, B_2} |\Phi(B_1, B_2)|_1 \tag{8}$$

where $|\cdots|_1$ is the L1-norm of the vector which contains all pairs of partiality and dissimilarity. Consequently, $D_S(\Omega_1, \Omega_2)$ measures the minimum distance from the origin $(0, 0)$ to the point on the Pareto optimum. The Salukwadze distance is then returned as the similarity value of managers Ω_1 and Ω_2.

5 EXPERIMENT

In this section, we evaluate the performance of the proposed manager matching method in an application. In order to do so, we designed an on-line experimental tool, transistorshead.com, to collect managerial actions from different managers. Then, based on the proposed manager representation model in Section 3.2, this platform represents each managerial action by different action features within different groups. Built on the represented manager, we apply the manager matching experiment and compare the matching results to the ground truths. Finally, the computational complexity of the proposed manager representation and matching methods are analysed and discussed.

5.1 Experimental Environment

In this paper, we developed a special tool: transistorshead.com, to record and represent managerial actions. This tool was designed based on the main idea in Section 3.1 and the following principles: (1) Every on-line management tool tracks and records managerial actions according to the idea of Unit of Behaviours (Curtis et al., 1992). (2) Using a management tool by a team manager is equal to an event occurring in an organisational environment which results in a thing (Flak, 2013). (3) Every on-line management tool is useful for describing managerial actions. With this tool, we record each managerial action and describe it with a 24-dimensional feature vector. Those features are grouped into 7 feature groups. It is interesting to point out that this tool can also be extended to represent managerial actions by content domain features. The detailed information is introduced in (Alnajjar and Flak, 2016).

With this tool, we have collected and built our dataset: PG-Manager. Specifically, in order to collect the managerial actions, 150 volunteers had been involved in our experiment over 15 months. The participants worked in small groups from different regions. Each group consists of a team manager and multiple members. Consequently, PG-Manager contains 56 managers and each manager contains 200 to 400 managerial actions. As introduced above, each action is represented by a 24-dimensional feature vector. This dataset is used to evaluate the proposed manager representation and matching methods in Section 5.2.

5.2 Manager Matching

In order to evaluate the proposed manager matching algorithm, we perform the managerial action sequence matching experiments on the PG-Manager dataset. Specifically, our evaluation is built on a retrieval framework where managers in the dataset are ranked based on their similarity to a query. Based on the ranked results and similarity values, we can distinguish different managers and also group them into

Table 1: Similarities between similar managers.

	Manager1	Manager2	Manager3	Manager4	Manager5	Manager6	Manager7	Manager8
Manager1	1	0.9919	0.9932	0.9797	0.9878	0.9702	0.9925	0.9706
Manager2	0.9919	1	0.9869	0.9868	0.9946	0.9769	0.9940	0.9704
Manager3	0.9932	0.9869	1	0.9702	0.9871	0.9708	0.9866	0.9766
Manager4	0.9797	0.9868	0.9702	1	0.9821	0.9749	0.9896	0.9705
Manager5	0.9878	0.9946	0.9871	0.9821	1	0.9702	0.9906	0.9721
Manager6	0.9702	0.9769	0.9708	0.9749	0.9702	1	0.9701	0.9724
Manager7	0.9925	0.9940	0.9866	0.9896	0.9906	0.9701	1	0.9703
Manager8	0.9706	0.9704	0.9766	0.9705	0.9721	0.9724	0.9703	1

different classes.

Table 1 illustrates the similarities between 8 managers. Those similarities are selected since they are above the threshold $\sigma = 0.97$. Considering the ground truth, these managers are similar to each other and belong to the same group. Therefore, the proposed method can correctly distinguish different managers. Moreover, compared to the ground truth in which only similar or dissimilar information is available, the proposed method not only provides such information, but also gives more accurate similarity scores. In such a case, scientists and practitioners can apply a deeper exploration in management science.

5.3 Computational Complexity

(1) For manager representation, the proposed method in Section 3.2 generally includes two parts: managerial actions and action features. For managerial actions, the time complexity is $O(M)$ since a manager Ω is composed by M actions. For a single action $\boldsymbol{a}$, since it can be represented by a T-dimensional feature vector, the time complexity is $O(T)$. Therefore, the total complexity is $O(MT)$. Recalling that in practice there are many more managerial actions than the number features ($M >> T$), the total complexity for manager representation is bounded by $O(M)$. (2) For manager matching, an exhaustive search over all possible matches for all possible block sizes has a complexity of $O(2^{N_1+N_2})$, where N_1 and N_2 are the number of actions within the two input managers. Our proposed approach based on integral image analysis enables matching in $O(N_1N_2)$ time. We implemented our method in Matlab, which enables manager matching on a Laptop within seconds.

6 CONCLUSION

In this paper, we propose a novel manager representation and matching algorithm based on managerial actions and their features. For manager representation, we firstly represent a manager by a action sequences collected by existing or the proposed tools. After that, each action is described by multiple time domain features within flexible feature groups. In such a case, the proposed representation method is flexible and general enough to cover most types of managers. For manager matching, based on the action sequences of managers, we first apply a partial matching method to search the matched blocks within action sequences. Then, the global similarities between managers are calculated built on their matched sequence blocks. In the future, we will extend our manager representation method by adding more types of managerial action and action features. In addition, we will try to implement the proposed algorithms for manager labelling based on the deep learning approaches.

ACKNOWLEDGEMENTS

Research activities leading to this work have been supported by the Chinese Scholarship Council (CSC) and the German Research Foundation (DFG) within the Research Training Group 1564 (GRK 1564). We greatly thank Frederic Li from University of Siegen for his significant help in our experiments.

REFERENCES

Abbott, A. (1990). A primer on sequence methods. *Organization science*, 1(4):375–392.

Al-Saleh, K. S. (2011). Productivity improvement of a motor vehicle inspection station using motion and time study techniques. *Journal of King Saud University-Engineering Sciences*, 23(1):33–41.

Alexandru, M. and Diana, M. (2015). Management skills assessment using 360 feedback-msf 360. *Procedia-Social and Behavioral Sciences*, 187:318–323.

Alnajjar, J. and Flak, O. (2016). Linguistic analysis of manager behaviour aimed at replacing human managers with robots. In *ECRMBMS*, pages 1–8.

Barnes, R. (1980). *Motion and Time Study; Design and Measurement of Work*. John Wiley, New York, USA, 8th edition.

Beaudry, P. and Francois, P. (2010). Managerial skills acquisition and the theory of economic development. *The Review of Economic Studies*, 77(1):90–126.

Bellman, R. (1954). The theory of dynamic programming. *Bulletin of the American Mathematical Society*, 60(6):503–516.

Beshears, J. and Gino, F. (2015). Leaders as decision architects. *Harvard Business Review*, 93(5):52–62.

Brink, C. and Rewitzky, I. (2002). Three dual ontologies. *Journal of Philosophical Logic*, 31(6):543–568.

Brinkerhoff, D. W. (1985). Managerial roles for social development management. *Public administration and development*, 5(2):145–156.

Brodie, M. B. (2007). Henri fayol: Administration industrielle et generate - a re-interpretation. *Public Administration*, 40(3):311–317.

Bronstein, M., Bronstein, M., Bruckstein, M., and Kimmel, R. (2009). Partial similarity of objects, or how to compare a centaur to a horse. *IJCV*, 84:163–183.

Crow, F. C. (1984). Summed-area tables for texture mapping. *ACM SIGGRAPH*, 18(3):207–212.

Curtis, B., Kellner, M. I., and Over, J. (1992). Process modeling. *Communications of the ACM*, 35(9):75–90.

Donoser, M., Riemenschneider, H., and Bischof, H. (2009). Efficient partial shape matching of outer contours. In *ACCV*, pages 281–292.

Dubuisson, S. (2010). The computation of the bhattacharyya distance between histograms without histograms. In *ICIPTTA*, pages 373–378.

Flak, O. (2013). Concept of managerial tools based on the system of organizational terms. In *IMPE*, pages 187–197.

Flak, O. (2015). Theoretical foundation for managers behavior analysis by graph-based pattern matching. *IJCM*, 12(4):110–123.

Flak, O. and Pyszka, A. (2013). Differences in perception of the participants in the management process and its real trajectory. *JEMI*, (4):35–72.

Halliday, R. M. and Stacey, M. J. (2009). Observation: The lost and found managerial skill. In *Northeast Decision Sciences Institute Proceedings*, pages 380–385.

Hensley, J., Scheuermann, T., Coombe, G., Singh, M., and Lastra, A. (2005). Fast summed-area table generation and its applications. In *Computer Graphics Forum*, volume 24, pages 547–555.

Hoegl, M. and Parboteeah, K. P. (2007). Creativity in innovative projects: How teamwork matters. *Journal of Engineering and Technology Management*, 24(1):148–166.

Karsten, L. (1996). Writing and the advent of scientific management: the case of time and motion studies. *Scandinavian Journal of Management*, 12(1):41–55.

Katz, R. L. (1974). Skills of an effective administrator. *Harvard Business Review*, 52(5):90–102.

Kirkpatrick, S., Gelatt, C. D., and Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, pages 671–680.

Koontz, H. and O'Donneil, C. (1964). *Principles of Management*, page 45. McGraw-Hill., New York.

Lopetegui, M., Yen, P.-Y., Lai, A., Jeffries, J., Embi, P., and Payne, P. (2014). Time motion studies in healthcare: What are we talking about? *JBI*, 49:292–299.

Magu, P., Khanna, K., and Seetharaman, P. (2015). Path process chart-a technique for conducting time and motion study. *Procedia Manufacturing*, 3:6475–6482.

Mathieu, J., Maynard, M. T., Rapp, T., and Gilson, L. (2008). Team effectiveness 1997-2007: A review of recent advancements and a glimpse into the future. *Journal of management*, 34(3):410–476.

Mintzberg, H. (1973). *The nature of managerial work*. Harpercollins College Div, New York: Harper & Row.

Mithas, S., Krishnan, M. S., and Fornell, C. (2005). Why do customer relationship management applications affect customer satisfaction? *JK*, 69(4):201–209.

Osada, R., Funkhouser, T., Chazelle, B., and Dobkin, D. (2002). Shape distributions. *ACM Transactions on Graphics*, 21(4):807–832.

Pavett, C. M. and Lau, A. W. (1982). Management roles, skills, and effective performance. In *Academy of Management Proceedings*, pages 95–99.

Perlow, L. (2014). Manage your team's collective time. *Harvard business review*, 92(6):23–25.

Russell, S. and Norvig, P. (2009). *Artificial Intelligence: A Modern Approach*. Prentice Hall Press, 3rd edition.

Shakshuki, E., Ghenniwa, H., and Kamel, M. (2003). An architecture for cooperative information systems. *Knowledge-Based Systems*, 16(1):17–27.

Siedlok, F. and Hibbert, P. (2014). The organization of interdisciplinary research: Modes, drivers and barriers. *IJMR*, 16:194210.

Sinar, E. and Paese, M. (2016). The new leader profile. *Training Magazine*, (46):46–50.

Sohmen, V. S. (2013). Leadership and teamwork: Two sides of the same coin. *Journal of Information Technology and Economic Development*, 4(2):1.

Spriegel, W. R., Myers, C. E., Gilbreth, F. B., and Gilbreth, L. M. (1953). *The writings of the Gilbreths*. RD Irwin.

Tengblad, S. (2002). Time and space in managerial work. *SJM*, 18(4):543–565.

Torsello, A. and Hancock, E. R. (2004). A skeletal measure of 2d shape similarity. *CVIU*, 95(1):1–29.

Viola, P. and Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. In *CVPR*, pages 511–518.

Whetten, D. and Cameron, K. (2016). *Developing management skills*. Prentice-Hall Project.

Yang, C., Tiebe, O., Grzegorzek, M., and Indurkhya, B. (2016). Investigations on skeleton completeness for skeleton-based shape matching. In *SPA 2016*. IEEE Signal Processing Society.

Yang, C., Tiebe, O., Pietsch, P., Feinen, C., Kelter, U., and Grzegorzek, M. (2014). Shape-based object retrieval by contour segment matching. In *ICIP*, pages 2202–2206.

Yang, C., Tiebe, O., Pietsch, P., Feinen, C., Kelter, U., and Grzegorzek, M. (2015). Shape-based object retrieval and classification with supervised optimisation. In *ICPRAM*, pages 204–211.