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# Learning Decision-Making Patterns in the Context of Manned-Unmanned Teaming

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***Abstract*—Manned-Unmanned Teaming (MUM-T) is an ensemble of manned and unmanned vehicles operating as a team to achieve the same set of goals. Such teaming is highly beneficial, notably in overcoming the limits of direct communication link to the unmanned vehicles, as well as in enhancing capabilities of a manned vehicle by leveraging multiple accompanying unmanned vehicles. However, this can in times overstrain the command and control capacity of the human operator(s) on board of the manned vehicle(s), unless if the unmanned vehicles possess some "understanding" of the human operators' decision-making behaviors, in which case, they can act like real "team players" to proactively support the manned vehicle, instead of waiting passively for successive commands. In this study, we investigate the possibility of learning decision-making behaviors of a human operator on board of a manned vehicle in charge of commanding multiple accompanying unmanned vehicles. We base our investigation on a rescue mission involving a manned helicopter and several unmanned aerial vehicles to collect training and validation data using software-in-the-loop simulations. By extracting meaningful features and by performing a clustering on the features on the training dataset, we validate and analyze the learned pattern of commanding the unmanned vehicles.**

***Index Terms*—manned-unmanned teaming, pattern matching, learning human decision-making behavior, unmanned vehicles, decision-making support**

## I. Introduction

Manned-Unmanned Teaming (MUM-T) is very promising for many future operations, as it leverages the proximity between the manned vehicle and unmanned vehicle to ensure continuous communication with the unmanned vehicles, while also increasing the operation radius of the manned vehicle without demanding more manpower [1]. Such a teaming configuration is especially beneficial in a rescue operation, where the disaster site is vast and response time is critical [2].

Although beneficial, it is challenging for the human operator(s) onboard of the manned vehicle to command (and control) the multitude of unmanned vehicles. The challenge is even more accentuated since the number of human operators in a manned vehicle is greatly reduced compared to the number of human operators that can be stationed in or near a ground control station. It is therefore essential to put forth an intelligent decision-support system on board of the manned vehicle to assist the human operators in commanding the unmanned vehicles.

For the sake of efficiency, the intelligent decision-support system must be designed in such a way, that it can anticipate the operators' behavior, so that the decision support provided is not limited to offline planning, which is mostly meant for longer-term plans requiring thereby sufficient knowledge about the dynamics of the environment over time [3], but also for online planning, where the operators make successive decisions to react according to the observations on the environment [2]. Being able to anticipate the operators' behavior will enable a delay-less strategic support (e.g. by moving closer to the next goal position before commanded), comparable to football players' anticipatory capabilities.

## II. Contributions

One of the main important features of a companion or assistance system is to be "human-aware". Besides generating multiple plans as guidance and leave the final decision to the human operator to make, as implemented in [3], another approach is to follow closely the current activities undertaken by the operator and provide, or suggest plans accordingly. Biundo et al. reviewed in [4] some of the recent research works in this aspect, while Honecker and Schulte implemented an online activity-determination function in [5] for manned-unmanned teaming.

However, most previous works focus on the online "human-awareness", and little on the knowledge gathered on the human operator's decision-making behavior. According to [6], anticipatory thinking consists of combining knowledge gathered from *pattern matching*, *trajectory tracking* and *conditional inference*. In this work, we focus on paving the way to enable anticipatory thinking of an intelligent decision-support system by implementing pattern matching approach based on an unsupervised learning method to predict the decision-making behavior of a human operator in charge of commanding the unmanned vehicles in MUM-T.

We first present a scenario based on rescue missions leveraging manned-unmanned teaming of aerial vehicles. The scenario is implemented and exploited for human-in-the-loop tests to collect data designated for training a pattern-matching approach to predict decision-making behavior, as well as for the validation of the trained patterns.

Subsequently, we describe the preprocessing of the features derived from the raw recorded data, as well as the classification and validation steps we adopted for pattern matching and prediction of the test persons' decision-making behaviors.

## III. Data Generation

In order to learn decision-making behaviors, human-in-the-loop tests must be conducted to collect training and validation data. For this purpose, a simulation environment based on Gazebo was constructed, alongside a command-and-control interface as illustrated in Figure 1 for the human operator onboard the helicopter to command the accompanying unmanned aerial vehicles (UAVs).

Given the large amount of data necessary for training the patterns, the simulated scenarios were implemented in an abstract manner in order to collect sufficient data within a reasonable amount of time.

### A. Scenario and problem statement

The rescue operation, on which the test scenarios are based, can be defined formally by the following tuple:

$$\mathcal{P} =< \mathcal{V}_{\mathcal{M}}, \mathcal{V}_{\mathcal{U}}, \mathcal{A}_{\mathcal{R}}, \mathcal{A}_{\mathcal{C}} >, \tag{1}$$

where $\mathcal{V}_{\mathcal{M}}$ is the set of manned vehicles $\{v_M^1, \cdots, v_M^M\}$, $\mathcal{V}_{\mathcal{U}}$ is the set of unmanned vehicles $\{v_U^1, \cdots, v_U^U\}$, $\mathcal{A}_{\mathcal{R}}$ is the set of risk areas $\{a_R^1, \cdots, a_R^R\}$ that require risk assessment or suppression (e.g. fire extinguishing), and $\mathcal{A}_{\mathcal{C}}$ is the set of critical areas $\{a_C^1, \cdots, a_C^C\}$ in which patients needing attention have been identified and must be rescued by the manned vehicle. Note that the cardinals of the sets $|\mathcal{V}_{\mathcal{M}}| = M$, and $|\mathcal{V}_{\mathcal{U}}| = U$ are constant, while $|\mathcal{A}_{\mathcal{R}}| = R$, and $|\mathcal{A}_{\mathcal{C}}| = C$ are variable, and are updated during the operations. The map in Figure 1 shows a manned vehicle (helicopter in blue), three unmanned vehicles (UAVs in blue, orange and yellow), the risk areas (circles in red) and the critical areas (circles in yellow).

Each risk area $a_R^r \in A_R$ is a tuple $< p_R^r, r_R^r, s_R^r >$, with $p_R^r$ and $r_R^r$ being the position and the initial radius of the area, and $s_R^r$ being the spreading rate of the area, i.e. the rate at which the radius $r_R^r$ increases. The spreading rate $s_R^r$ is not known numerically to the human operator, but can only be visually perceived through the map on the command and control interface. Each critical area $a_C^c \in A_C$ is a tuple $< p_C^c, r_C^c, m_C^c, n_C^c, c_C^c >$, with $p_C^c$ and $r_C^c$ being the position and the (constant) radius of the area, $m_C^c$ being the number of missing patients to search for, $n_C^c$ being the number of found patients to rescue, which if left unattended for a longer time[1] will decrease, as the patients will be considered "deceased", and $c_C^c$ being the number of casualties of the critical area $a_C^c$.

### B. Implementation

The scenario based on the problem statement describe above with $M = 1$, and $U = 3$ was implemented using Gazebo [7], an open-source three-dimensional simulation engine, and ROS (Robot Operating System) [8]. Gazebo is used for simulating 1) the physics and sensors of the manned and unmanned vehicles, as well as 2) the objects and the terrain of the environment, while ROS is exploited mainly for the inter-process-communication, to *publish* and *subscribe* messages on *ROS-Topics* related to the command of a vehicle, sensor data, visualization data and autonomous piloting data (for the UAVs) via a synchronized *request-response* manner.

[1]The duration of which a patient waiting to be rescue can live varies randomly. In general, patients of a critical area far away from a risk area (e.g. a fire) tend to have longer survival duration.

While each UAV has an autopilot function, requiring therefore only a goal risk/critical area set when commanded by the operator, the helicopter has to be piloted manually. In our tests, the human operator of the UAVs is also the pilot of the helicopter.

### C. Data Collection

Human-in-the-loop tests with two test persons were conducted to collect training and validation data. The objectives of each test are identical:

- to reduce the spread of risk areas by commanding an unmanned vehicle to operate there;
- to minimize casualties by finding the missing patients in the critical areas as soon as possible (using UAVs) and by rescuing the found patients by using the manned vehicle.

The size of the areas is scaled and the operating duration is fast-forwarded, so that each test mission spans over a duration of 15 to 20 minutes, yet contains sufficient moments where decisions of assigning UAVs to risk/critical areas must be made. Keeping the test missions reasonably short ensures that the test persons stay focused. However, when a discrete event is triggered (e.g. a new risk/critical area appears, a command for a UAV is set, or new missing patients are reported), the time frame will be frozen to allow the test person to read the the alert messages (see Figure 2). In total, 15 test missions were implemented. Furthermore, to avoid overwhelming the test persons, the number of risk areas $R$ varies between 4 to 6, while the number of critical areas $C$ varies between 4 to 5, with each having between 4 to 15 patients to rescue, i.e. $m_C^c \in \{4, 5, \cdots, 15\}$.

Observations on the test missions (i.e. current position of the manned vehicle, current and (commanded) goal positions of the UAVs, position and radius of the risk areas, as well as position, radius, the number of patients and the number of casualties of each critical area) were recorded every three seconds in a JSON-file [9]. Moreover, at each triggered discrete event (e.g. new risk area, new command for the UAV, newly reported missing patient, newly reported casualty), observations on the events will be recorded instantaneously without awaiting the three-second interval.

## IV. Behavior Classification

Using the data generated and collected from the human-in-the-loop tests, we use k-means to cluster the behaviors of the test persons as operators, to study their decision-making patterns in commanding the UAVs. K-means algorithms have been widely used in medical field to derived patterns linked to diseases [10], but also in the study of human behavior, for example in the modelling of consumers' behaviors [11].

### A. Preprocessing of Features

The recorded observations first undergo a preprocessing step to exclude irrelevant data by hand, and to devise *meaningful* features from existing observation data. The features considered after this step are listed in Table I and II. Note that each feature is a vector of feature data of the same length as the observation data.

In addition to the features listed in the tables, a feature $f_S$ is also considered, which represents if the operator

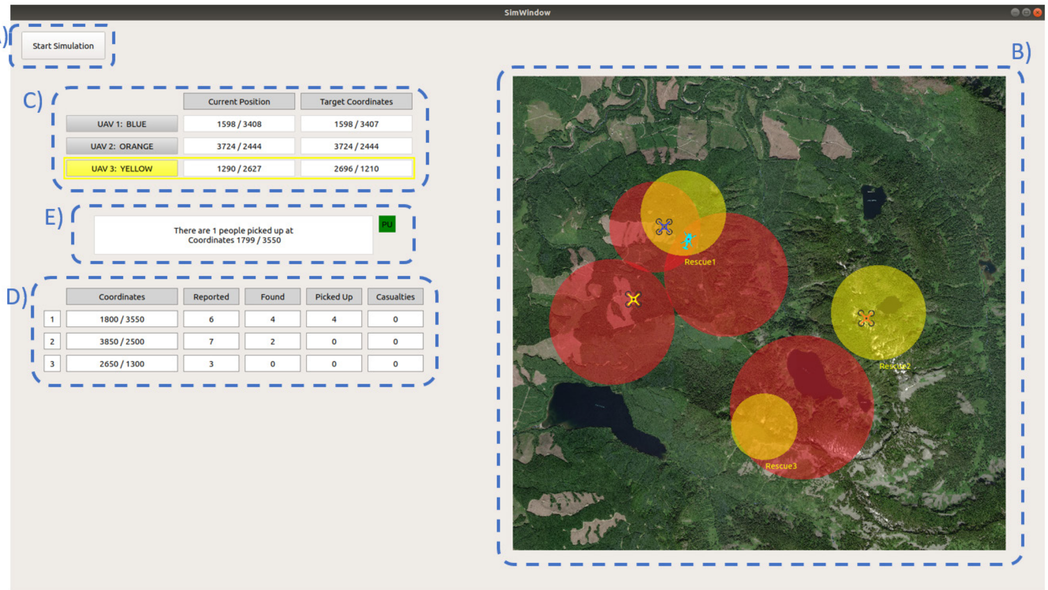



Fig. 1: Command and control interface for MUM-T in a large-scale rescue operation: A) is the button to start the mission simulation, B) is the map visualization, C) is the information on the positions of the UAVs and their assigned positions (without unit as the simulation works in a miniaturized world), D) is the list of critical areas, while E) is a window for information display.

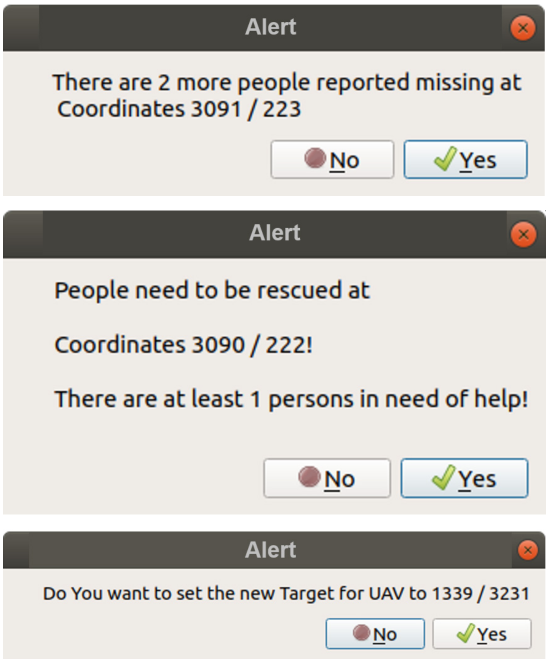



Fig. 2: Alert messages on newly reported missing patients, a new critical area, confirmation of a newly assign goal for a UAV.

TABLE I: Features extracted related to a risk area

| Symbol | Meaning | Raw/Devised data |
|---|---|---|
| $f_R^1$ | Spread rate | Raw |
| $f_R^2$ | Radius | Raw |
| $f_R^3$ | Number of overlapping risk areas | Devised |
| $f_R^{4,u}$ | Distances to the unmanned vehicle $v_U^u$ | Devised |

TABLE II: Features extracted related to a critical area

| Symbol | Meaning | Raw/Devised data |
|---|---|---|
| $f_C^1$ | Time passed since the critical area appears | Devised |
| $f_C^2$ | Number of patients to be rescued | Raw |
| $f_C^3$ | Number of missing patients to search | Raw |
| $f_C^4$ | Number of casualties | Raw |
| $f_C^5$ | Number of overlapping risk areas | Raw |
| $f_C^6$ | Quotient of areas[2] | Devised |
| $f_C^{7,u}$ | Distance to the unmanned vehicle $v_U^u$ | Devised |

commands one of the UAVs to a new goal (risk or critical) area. This feature is known as *switch* to indicate that a decision ist made proactively by the test person.

Note that many selected features are devised from the recorded raw observation data recorded. These devised features are considered more significant to the cognitive capabilities of a decision maker. For example, the positions of the risk/critical areas are not representative for the mission operator, while the relative distances to the UAVs (i.e. $f_R^4$ and $f_C^6$) are factors that can influence if and which UAV will be assigned to the area. Likewise, the time at which a critical area appears is unimportant compared to how much time has passed (i.e. $f_C^1$). Another deciding factor is the number of risk areas that overlap (i.e. $f_R^3$), since the overlapping and high density of red circles on the command interface may incite a cognitive urgency.

### B. Classification Method

The goal is the learn the pattern that can be used to predict when a "switch" decision (i.e. proactive assignment of a UAV to a risk/critical area) will be made.

For this purpose, an unsupervised learning method, i.e. k-means clustering, will be exploited. The set of features $\mathcal{F}$

will first undergo preprocessing and then clustering to learn the behavior of the mission operator (see Algorithm 1).

**Algorithm 1** Preprocessing of data and $k$-means clustering to learn and predict the decision-making behavior of a test person

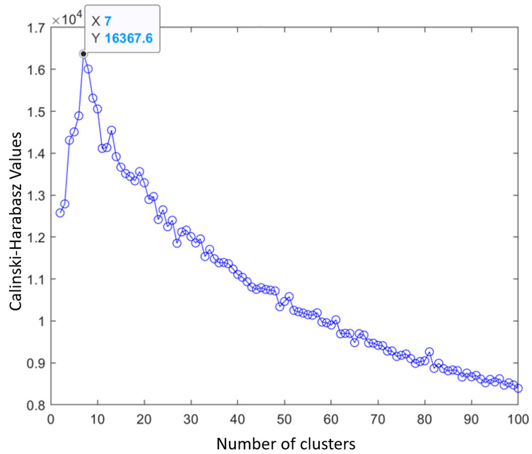
**Require:** The set of features considered $\mathcal{F}$
1: **for all** features $f_*^n$ **do**
2: scale the features with $\bar{f}_*^n = (1/\sigma_{f_*^n})(f_*^n - m_{f_*^n})$
3: **end for**
4: divide the scaled data into training data $\mathcal{R}$ and validation data $\mathcal{V}$
5: determine $\tilde{k}$, the estimated optimal number of clusters, using Calinski-Harabasz Criterion
6: **for all** $k \in \{\tilde{k} - n_k, \cdots, \tilde{k} + n_k\}$ **do**
7: perform $k$-means clustering to determine the $k$ clusters
8: compute the probability of a *switch* decision in each trained cluster $p_i^T$, where $i \in \{1, \cdots, k\}$
9: **end for**
10: **for all** $k \in \{\tilde{k} - n_k, \cdots, \tilde{k} + n_k\}$ **do**
11: assign each observation in the validation data $\mathcal{V}$ to the nearest cluster (of the $k$ clusters)
12: compute the probability of a *switch* decision in each cluster made up of only the validation data $p_i^V$, where $i \in \{1, \cdots, k\}$
13: **end for**

Each feature will be scaled with $(1/\sigma_{f_*^n})(f_*^n - m_{f_*^n})$, where $m_{f_*^n}$ is vector of repeated mean value of $f_*^n$ and $\sigma_{f_*^n}$ the scalar standard deviation. The scaling is to ensure a comparable order of magnitude of all data used in the clustering (see Line 2). To avoid over-fitting, the scaled features are subsequently divided into training data $\mathcal{R}$ and validation data $\mathcal{V}$ (see Line 4). In practice, we retained feature data of 3 test missions for validation, while the rest were used for training. To perform the k-means clustering on the training data $\mathcal{R}$, we first need to determine the estimated optimal number of clusters $\tilde{k}$. This is done by using the Calinski-Harabasz Criterion [12] in Line 5 (see Figure 3 for the estimation of the optimal number of clusters). Note that $\tilde{k}$ is only an estimation, since the numerical validation suggests otherwise. However, the estimated optimal number of clusters $\tilde{k} = 7$ provides a reasonable indication to guide our clustering; therefore, we perform clustering for a number of clusters in the neighborhood of $\{\tilde{k} - n_k, \cdots, \tilde{k} + n_k\}$, as described in Line 6 to 9. Meanwhile, the probability $p_i^T$ of a "switch" decision be made within each determined cluster $i$ is computed.

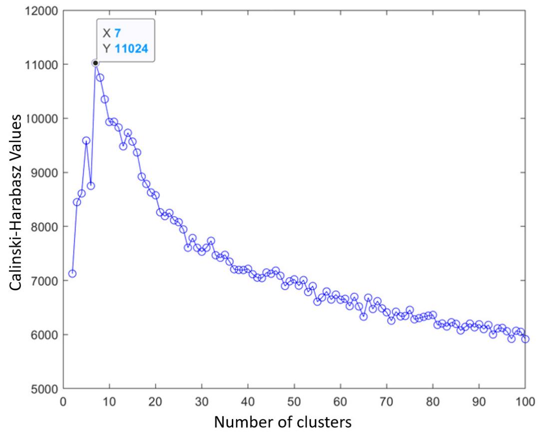
To validate, as described in Line 10 to 13, each feature observation of the validation dataset $\mathcal{V}$ will be assigned the nearest cluster among the trained $k$ clusters. The probability of a "switch" decision $p_i^V$ of the clustered validation features will be determined. If for each $i \in \{1, \cdots, k\}$, $|p_i^V - p_i^T| < \epsilon_p$, the learning of decision-making pattern is considered successful.

## V. Classification Results

The goal of the work is to learn the pattern with which the human operator decides to re-assign or "switch" a UAV to a risk/critical area. The learning was conducted separately, on




(a) Assessing Calinski-Harabasz values for risk areas




(b) Assessing Calinski-Harabasz values for critical areas

Fig. 3: Analysis using Calinkski-Harabasz values to search for the optimal number of clusters

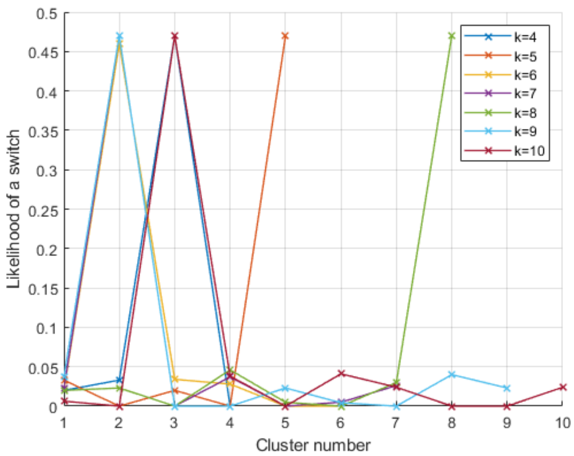
the pattern to *switch* a UAV to a risk area, and on the pattern to *switch* a UAV to a critical area.

Figure 4a depicts the likelihood of switching a UAV to a risk area within each cluster using the following:

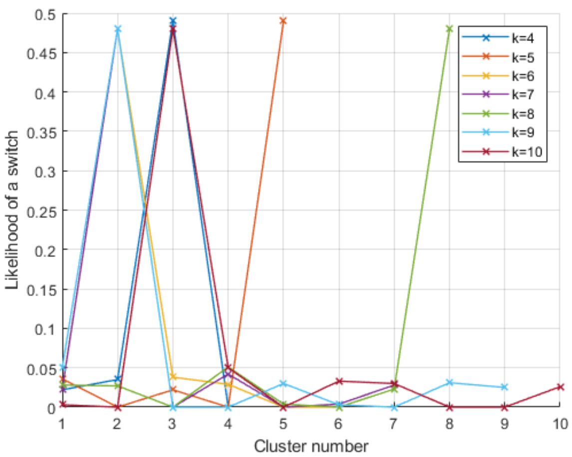
$$L_i = n_{f_s}/n_i, \tag{2}$$

with $i$ being the cluster number, $n_{f_s}$ being the number of switch detected and $n_i$ being the total number of data points of cluster $i$. The likelihood-evaluation was conducted for different number of clusters $k$. It is observed that for each $k$, there is an identifiable cluster of which the likelihood of a switch is more substantial than the likelihood obtained from other clusters. While Figure 4a was obtained using the training data collected from the human-in-the-loop tests with P2, Figure 4b was obtained using the validation data from P2. Both likelihood plots are comparable.

We based further evaluation using $k = 5$, i.e. all data are clustered into five clusters. The selection of $k$ is based on the quotient $q_k = L_{i_1}/L_{i_2}$, where $i_1$ is the cluster number with the most substantial likelihood among all clusters determined with a given $k$, while $i_2$ is the cluster number with the second most substantial likelihood among all clusters determined with a given $k$. $q_k$ is the most substantial for $k = 5$ highest, as shown in Figure 5. We evaluate subsequently the transferability of the learned clusters (i.e. pattern) from test person P2 to test person P1, by comparing the likelihood of a switch to a disaster area obtained using all collected data from both test persons for $k = 5$, as depicted in Figure 6. It is observed that the clusters (i.e. patterns) learned to know how likely both test persons will switch a UAV to a disaster area are comparable, confirming therefore the transferability of the learned decision-making behavior for different operators.




(a) Likelihood of a switch to a risk area for different $k$ obtained using the training data collected from P2




(b) Likelihood of a switch to a risk area for different $k$ obtained using the validation data collected from P2

Fig. 4: Likelihood of a switch to a risk area for P2

Similar evaluations were performed on the switch of a UAV to a critical area. Figure 7a shows the likelihood of switching a UAV to a critical area for each cluster $i$. The test was conducted using different numbers of clusters $k$, and using *all* collected data from test person P2. Again, for each number of clusters $k$, there is one identifiable cluster of which the likelihood is more substantial (except for $k = 4$). By evaluating the quotients for all $k$ obtained using Equation 2, we compare the "transferability" of the learned behaviors of test person P2 to test person P1. It is observed in Figure 7c that the decision-making behavior of P2 and P1 are similar, when it comes to switching a UAV to a critical area.

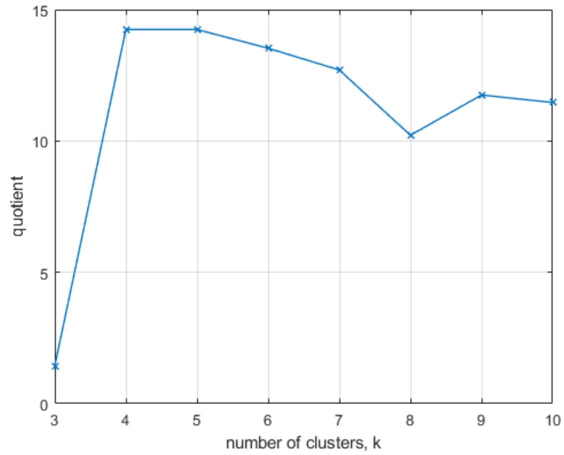



Fig. 5: Quotient of the most and second most substantial likelihood of a switch to a risk area for different $k$ obtained using the training data collected from P2

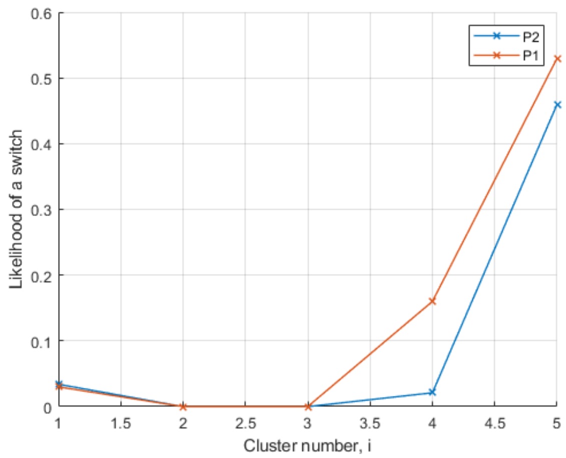



Fig. 6: Comparing the likelihood of a switch to a risk area for P2 and P1

## VI. Conclusion

In this work, we used the k-means clustering to derive decision-making patterns, which can be exploited to predict the behavior of the test person. The method was developed and tested on a use case based on a manned-unmanned teaming in a rescue operation. It is essential to note that the features used for training the clusters are derived by considering relative quantities, which cognitively speaking, are more observable and meaningful for a human operator.

The ability of predicting the decision-making behavior of the human operator on board of the manned vehicle commanding multiple unmanned vehicles will be beneficial in enabling the unmanned vehicles to anticipate the intention of the commanding operator. This will in return reduce response time to a task assignment or can even automatize task assignments, should the commanding operator be incapacitated.

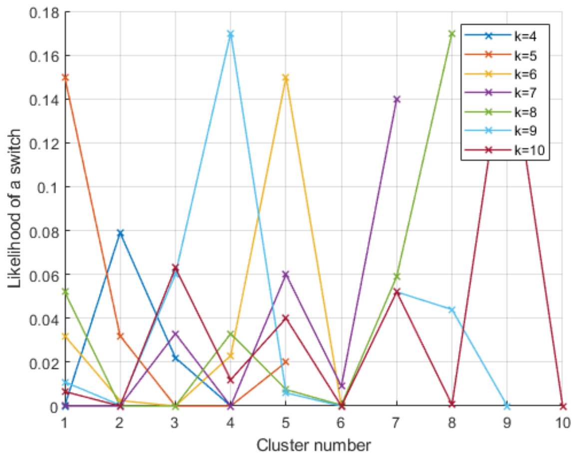
### A. Future Work

This article reports mainly on a preliminary study conducted prior to developing anticipatory thinking for unmanned vehicles which are supposed to collaborate as teammates of manned vehicles in a MUM-T operation. The results obtained are limited to only "pattern matching" in anticipatory thinking.

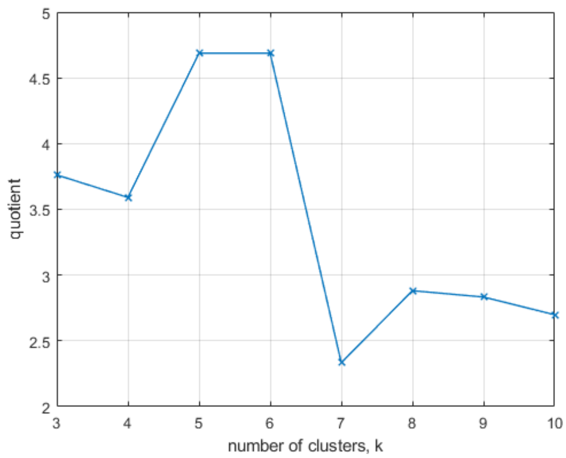
Future works should focus on exploiting other means to achieve anticipatory thinking (i.e. "trajectory tracking" and "conditional inference"). The exploitation of these means to enhance the autonomy of the unmanned vehicles must also be investigated in the future.

Furthermore, more use cases, including those with moral conflicts, should be considered in developing the approach for "pattern matching". We observe that the learned pattern is transferable for another person in the use case considered in this study, which may no longer be the case, should the use case be richer in moral conflicts. However, we collected the data for only two test persons with rather similar backgrounds (i.e. male test persons of comparable age and similar education backgrounds). The "transferability" may also not be always true, if a bigger and more diverse group of test persons is used for the tests.

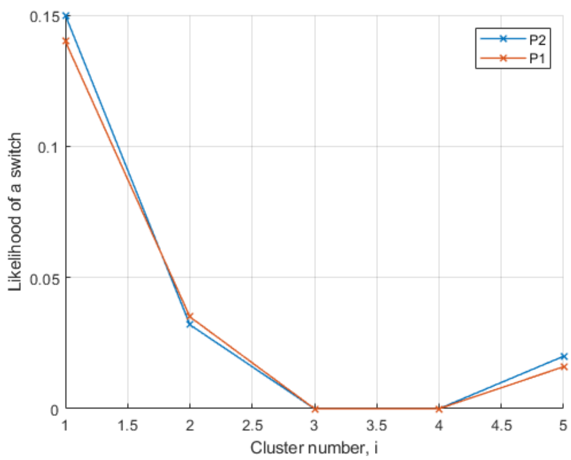
Lastly, this work provides only a method for *pattern matching*. Other contributing capabilities for anticipatory thinking can be further considered, such as *trajectory tracking* [13] or *conditional inference* [14].




(a) Likelihood of a switch to a critical area for different $k$ obtained using the all data collected from P2




(b) Quotient of the most and second most substantial likelihood of a switch to a critical area for different $k$ obtained using all data collected from P2




(c) Comparing the likelihood of a switch to a rescue area for P2 and P1

Fig. 7: Likelihood of a switch to a critical area and the transferability of the learned clusters

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