Coordination of Communication in Distributed Sensing Systems

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Abstract

This paper describes an algorithm for coordination of communication of probabilistic information in distributed sensing systems. We envision the distributed sensing system as a team of observers, each of which observes locally and communicate with other members in order to improve its local estimation. Due to the limited communication bandwidth and constraints imposed by the network topology, communicating all information with each other is inefficient/infeasible. By quantifying information which is communicated among the members, the problem of coordination of communication is considered in the framework of *team decision theory*. By maximizing the expected overall information throughput in the distributed sensor network under resource and topological constraints, decisions rules can be obtained for each sensor member on "how much to communicate". Two simple examples of distributed tracking system are presented.

1 Introduction

The problem of coordination of communication can be broadly considered in the context of distributed estimation and control[14] and distributed Artificial Intelligence[5, 11]. In this paper we attempt to address this problem using the *team decision theory*[7]. How much to communicate is regarded as a decision to be made by each individual member. Information possessed by individual members is intrinsically uncertain and correlated. The aim of the team is to maximize the expected information flow within the system under bandwidth and topological constraints.

Team decision theory originated from problems in game theory[12] and multi-person control[7, 6]. Game theory is mainly concerned with problems where each player is trying to maximize its own utility while minimizing that of its opponents. In the area of cooperative game the problem is much more complicated due to the interactions between players. Team theory considers the cooperative game problem when all the players only have common interests. The members of the team may have different information with regard to some underline situation, but their actions must further the interests of the whole team. Therefore the objective of the team is to make the optimal decision for all possible information about the state of the problem obtained by individual team members.

The problem of coordinating communication of information in a distributed system can be address adequately by the team decision theory. We propose to describe a distributed sensing system as a team of observers, each of which makes local observations on some situations of common interest. It is clear that these observations are uncertain yet correlated. Each member must therefore communicate with other members in order to improve its estimation of the state of the world. In the case where communication can be achieve instantly and without cost, it can be shown that global optimal estimation, as defined in a centralized system, can be obtained for each member[9]. In reality limited communication bandwidth and topology constraints imposed by the system architecture does not permit instant and free communication. Therefore decisions have to be made by each member on whether assimilation of information from other member is needed. On the whole, their actions must further certain common interest defined by the team, such as maximizing the information throughput in the network.

The rest of the paper is organized as follows: In Section 2 the general problem of estimation control is introduced and algorithms for solving this problem is briefly introduced. In Section 3 team theory is introduced. A simple example is used to illustrate the concept of team theory. In section 4 information metrics is defined using the notion of entropy. Decentralized estimation, based on the information filter, is also introduced. In Section 5 we present a general framework for coordinating communication of information in distributed sensing systems. An example of coordinating communication of information, defined by the information filter, is presented. Finally in section 6 discussions of applying team theory to multistage decision making and asynchronous communication is discussed.

2 Estimation and Control

In the following, the general problem of distributed estimation and control is described. A brief survey of algorithms and the class of problems which can be solved by these algorithms are presented.

From the estimation and control point of view, a distributed system can be described as a network of observers and control units (or Decision Makers (DM)). Let us assume that the number of DMs is N ($N > 0$) and the system only operates for a limited time steps $T, (T > 0)$. Observations are made and controls are applied at each time step from these nodes. Without losing generality, at time step t, each node i makes a local observation $\mathbf{z}_t^i$ and applies a local control $\mathbf{u}_t^i$. The operation of the system can be described as follows:

- At time step 0:
  - System assume initial state $\mathbf{x}_0$.
- At time step 1:
  - Observations $\mathbf{z}_1^1, \cdots, \mathbf{z}_1^N$ are made at each node.
  - Controls $\mathbf{u}_1^1, \cdots, \mathbf{u}_1^N$ are applied at each node.
  - System transits to state $\mathbf{x}_1$.
- ....
- At time step t:
  - Observations $\mathbf{z}_t^1, \cdots, \mathbf{z}_t^N$ are made at each node.
  - Controls $\mathbf{u}_t^1, \cdots, \mathbf{u}_t^N$ are applied at each node.
  - System transits to state $\mathbf{x}_t$.
- ....
- Transition to state $\mathbf{x}_T$.

The uncertainties concerning operation of the system are modeled by a set of independent random vectors with given probability distributions:

$$\mathbf{x}_0; v_t^n, w_t^n (t = 1, \cdots, T; n = 1, \cdots, N).$$

where v_t^n is the noise associated with the state transition and w_t^n is the observation noise. The variables are related by the state transition equations

$$\mathbf{x}_t = f_t(\mathbf{x}_{t-1}, v_t, \mathbf{u}_t^1, \cdots, \mathbf{u}_t^N), t = 1, \cdots, T$$

and the observation equations

$$\mathbf{z}_t^n = g_t^n(\mathbf{x}_{t-1}, w_t^n), n = 1, \cdots, N; t = 1, \cdots, T.$$

A loss function can be defined by the expression

$$\sum_{t=1}^{T} h_t(\mathbf{x}_t, \mathbf{u}_t^1, \cdots, \mathbf{u}_t^N). \qquad (1)$$

Note that the decision problem is not to find a sequence of $\mathbf{u}_1, \cdots, \mathbf{u}_T$ which minimizes the expected loss described by Equation 1, which is not probabilistically well defined if the decision rules are not specified. In general it is an optimization problem on functionals $(\mathbf{u}_1, \cdots, \mathbf{u}_T)$. One must therefore specify the possible ways in which the control variables are generated so that the lost function will be well defined.

The problem of finding the best decision rules (or strategies) is usually considered as planning in AI. In control theory the most popular results are those for unconstrained control of linear systems with Gaussian noise and quadratic criteria and classical information pattern[14]. In this case it is possible to separate the problem of estimation and control. In other words, the control problem can be divided into two steps:

- A filtering algorithm independent of control rules to obtain the optimal estimation;
- Control policies based on the optimal estimation.

For non-linear systems with finite decision rules and states dynamic programming algorithm can be used. However the general problem of designing optimal control strategies remains unsolved.

In distributed systems the problem is further complicated because instant communication among the nodes is not always possible. Team decision theory[7] was introduced to deal with the above problem. Each team member makes a local decision based on its local observation on the state of the world. The probabilistic distribution of the state vector is assumed to be known. However no communication of observation is allowed among the members. The team theory states that optimal decision rules can be obtained by maximizing the expectation of some pre-arranged global utility function. It is, however, only concerned with one step decision problems[1].

On the other hand distributed estimation algorithms based on the Decentralized Kalman Filter(DKF) and the Extended DKF (for non-linear systems)[9] have been developed. Each node updates its local estimation based on its local observations and local state transition model. An assimilation step is then introduced to obtain global optimal estimation at each node. No centralized fusion centre is needed. Information filter[8], which is based on the Kalman filter but updates an information state vector and an information matrix, has also been developed. However, assimilation requires communication from every other node. In general, this is limited by the communication bandwidth and network topology.

It is, therefore, desirable to consider situations where communication might be an option for the local node to choose. Consider a distributed system, each node updates its local estimation based on its local observations. It then decide whether to act on the local estimation (without further communication) or to act on assimilated estimation (with communication from other nodes). This is plausible since communication are not freely available, therefore team members must coordinate so that the overall information flow in the system is maximized.

3 Team Decision Theory

Team theory was introduced in [7] to describe the problem of decentralized statistical decision making in economic systems. A team of decision makers have access to different information concerning the underlying uncertainties.

[1]The extensions of team decision theory to multi-stage problems[6] can be regarded as the general multi-stage decision problem since complete recall are allowed

Each member makes local decisions based on its local observations. The aim is to find the optimal decision rules for each members so that the expected utility of the team as a whole is maximized.

3.1 Problem Statement

We will first briefly introduce the team theory in the framework of the general estimation and control problem described in the previous section and then follow it with a simple example.

A random vector $\mathbf{x}$ with known distribution, described by its Probability Distribution Function (PDF) $p_x(\mathbf{x})$, is used to represent all the uncertainties that have bearing on the problem we are considering. A set of observations $\mathbf{Z} = [\mathbf{z}_1, \cdots, \mathbf{z}_N]$ with

$$\mathbf{z}_i = m_i(\mathbf{x}), i = 1, \cdots, N \tag{2}$$

is obtained by each member. A set of decision variables $[\mathbf{u}_1, \cdots, \mathbf{u}_N]$ is also defined. The variables $\mathbf{x}, \mathbf{z}_i$ and $\mathbf{u}_i$ are all assumed to take values in appropriate spaces $\Xi, \mathbf{Z}, \mathbf{U}$. The strategy (decision rule, control law) of the ith member is a map $\gamma_i : \mathbf{z}_i \rightarrow \mathbf{u}_i$ which can be interpreted as a plan of which decision to take under what circumstances (observations):

$$\mathbf{u}_i = \gamma_i(\mathbf{z}_i) \tag{3}$$

The loss is defined as a map $L : \Xi \times \mathbf{U} \rightarrow \mathbf{R}$, i.e.,

$$Loss = L(\mathbf{u}_1, \cdots, \mathbf{u}_N, \mathbf{x}). \tag{4}$$

Note that the integration or the expectation of the Loss is meaningful only when the decision rules $\gamma_i(\cdot)$ are specified. For a given set of strategies tuples $\gamma_i, i = 1, \cdots, N$, L is a well-defined function of the state vector $\mathbf{X}$, i.e.,

$$L(\mathbf{u}_1, \cdots, \mathbf{u}_N, \mathbf{x}) = L(\cdots, \mathbf{u}_i = \gamma_i(m_i(\mathbf{x})), \cdots, \mathbf{x}).$$

Thus the expectation of L with respect to $p_X(\mathbf{x})$ is well defined. Finally the team decision problem can be described as

Find $\gamma_i(\cdot) \in \Gamma, \forall i$ in order to minimize

$$J = E_{\mathbf{X}}[L(\cdots, \mathbf{u}_i = \gamma_i(m_i(\mathbf{x})), \cdots, \mathbf{x})] \tag{5}$$

In general the above formulation is conceptually simple but practically very difficult to solve since it is a function optimization problem and J is a functional. However, by further restricting the class of problems it is possible to solve the above problem. Examples include parameterization or allowing only finite decisions.

3.2 A Robot "Shepherd"

Consider a mobile robot armed with a tracking camera and a ring of sonar sensors trying to keep track of a "lamb". The tracking mechanism of the camera is implemented independently from that of the robot motion, i.e., the camera is programmed to track a moving target from any position. On the other hand the control of the robot motion is dictated by the sonar bumper for real time obstacle avoidance and following. The task of the robot "shepherd" is to track and keep a reasonable distance to a moving "lamb".

The two sensor system must cooperate in order to track and follow the moving target due to the following reasons:

- The vision system tracks the target with accurate angular estimation but poor distance estimation. The turning angle depends on both angular and range estimations.
- The vision system can be affected by background textures.
- The infra-red and sonar system tracks the target with more accurate range estimation than angular estimation. The motion of the base depends on both angular and range estimations.
- The infra-red and sonar system can be affected by specularity and other factors.

In order to track and follow the target effectively both systems must make decisions as fast as possible so that they will not miss the target. On the other hand, when the local estimation of the target position becomes uncertain due to various reasons it is desirable to communication with each other so that more effective actions can be taken. However, communication comes with costs and will slow down the control of both systems. It is, therefore, desirable to find the optimal decision rules for both sensor systems, so that the expected loss some common concern is minimized.

3.3 Communicate or Not Communicate?

To simplify the formulation and clearly demonstrate the concept we shall only consider a one-step ahead situation. The decision rules are also discrete and so it the set of possible state of the world.

The state of the world $\mathbf{x}$ is either "tracked" or "not tracked". Both the tower and the base maintains their own local estimates of the state of the world, $\mathbf{x}_b$ and $\mathbf{x}_t$. They take value as either "tracked" or "not tracked". It is assumed that the joint distribution of the above random variables is known (see Table 1).

Target tracked

base \ tower	comm.	not comm.
comm.	-8	-3
not comm.	-3	6

Target missed

base \ tower	comm.	not comm.
comm.	10	-3
not comm.	-3	-8

Table 1. Loss function table

Each member (the tower and the base unit) takes a local observation, and update $\mathbf{x}_b$ and $\mathbf{x}_t$ respectively. The decisions, $u_b = \gamma_b(\mathbf{x}_b)$ and $u_t = \gamma_t(\mathbf{x}_t)$, available to both members are either "request communication" or "not request communication". We consider four possible combinations: none requests communication; tower requests communication; base requests communication;both request communication. We assume that only the member who requests communication pays for the communication. In other words, the requesting member has to obtain the information from other members and update its own estimate. One possible decision rule can be based on the variance of the local estimate $E(\mathbf{x}_b - E(\mathbf{x}_b))^2$. If the variance exceed certain threshold the member decide to request communication from other members.

We associate a cost matrix with respect to the decision pairs and the state of the world (see Figure 2). The assignment of costs are arbitrary in this case, but it is not difficult to calculate them from certain physical quantities, such as the time delay cost when communication is needed and the costs due to the variance.

t–tracked; m–missed

$\mathbf{x}$	t	t	t	t	m	m	m	m
$\mathbf{x}_b$	t	t	m	m	t	t	m	m
$\mathbf{x}_t$	t	m	t	m	t	m	t	m
Prob	0.25	0.05	0.1	0.1	0.1	0.1	0.05	0.05

Table 2. Joint probability distribution of the state $\mathbf{x}$ and the individual observations

The expected loss for any γ_b and γ_t is

$$J = \sum_{\mathbf{x}} L(u_b = \gamma_b(\mathbf{x}_b), u_t = \gamma_t(\mathbf{x}_t), \mathbf{x}) Pr(\mathbf{x}_b, \mathbf{x}_t, \mathbf{x}) \quad (6)$$

By enumeration it is not too difficult to find the optimal decision rule for the robot "shepherd".

4 Information and Decentralized Estimation

In the previous section we presented a very simple example of using team theory to find the optimal decision rules in order to coordinate communication in a distributed system. The loss function and decision rules are somewhat contrived but nevertheless demonstrates the need for coordinated communication when communication is itself an action which incur losses. Statistical estimation algorithms such as those based on Decentralized Kalman Filter[9] (DKF) requires each node to communicate its local information with other nodes in order to obtain a global optimal estimation. In reality, however, the communication bandwidth and the network topology will limit the amount of information which can be communicated. In the following we shall introduce the notion of information based on entropy as a quantitative measure of information contained in the random variables. Observation is therefore a process of "gathering" information (or reducing entropy). We shall describe how information are "gathered" and communicated among the node of a distributed system using the notation of the DKF.

4.1 Measures of Information

Before we attempt to coordinate communication it is necessary to define clearly what is being communicated. Since the state of the world that we are interested in is described by a random vector with probabilistic distribution, it is natural to use entropy, or sometimes known as Shannon information[10, 3], as the measure of information contained in that random vector.

Information can be defined as the expectation of the log-likelihood of a PDF[10, 4, 3]

$$I(p(\mathbf{x})) \triangleq E\{\ln p(\mathbf{x})\}. \quad (7)$$

Similarly we can define the entropy of the posterior distribution of $\mathbf{x}$ given observation $\mathbf{z}(k)$ at time k, defined by the Bayes Theorem, as follows

$$I(k) \triangleq h(p(\mathbf{x}|\mathbf{z}(k))\ln p(\mathbf{x}|\mathbf{z}(k))d\mathbf{x}. \quad (8)$$

Let $\mathbf{z}^k$ denote the collection of observations up to time step k and $\mathbf{z}(k)$ the observation at teim step k, i.e.,

$$\mathbf{z}^k \triangleq \{\mathbf{z}(1), \cdots, \mathbf{z}(k)\}.$$

Applying the Bases Theorem one more time we can obtain

$$\begin{aligned} E\{\ln[p(\mathbf{x}|\mathbf{z}^k)]\} &= E\{\ln[p(\mathbf{x}|\mathbf{z}^{k-1})]\} & (9) \\ &+ E\left\{\ln\left[\frac{p(\mathbf{z}(k))|\mathbf{x}}{p(\mathbf{z}(k)|\mathbf{z}^{k-1})}\right]\right\} & (10) \end{aligned}$$

Let $I(\mathbf{x}, \mathbf{z}(k))$ denote the information about $\mathbf{x}$ contained in the observation $\mathbf{z}(k)$, i.e.,

$$i(k) = I(\mathbf{x}, \mathbf{z}(k)) \triangleq E\left\{\ln\left[\frac{p(\mathbf{z}(k)|\mathbf{x})}{p(\mathbf{z}(k))}\right]\right\} \quad (11)$$

Note that the observations are assumed to be uncorrelated sequence. The information relationship for Bayes theorem can be rewritten simply as

$$I(k) = I(k-1) + i(k). \quad (12)$$

or

posterior $\mathbf{I}$ = prior $\mathbf{I}$ + $\mathbf{I}$ in observations.

It is not difficult to see the relationship between information contained in the random variable and the variance of the variable from Equation 7. In the case of a random vector, the information contained in the random variable is related to the covariance matrix.

Using the above notion of information, an information filter, which is simply a Kalman filter recast in terms of the information-state vector[8], can be obtained. The information matrix is simply the inverse of the covariance matrix.

In order to show how the above information definition can be used in practical estimation process let us consider a system described in linear form:

$$\mathbf{x}(k) = \mathbf{F}(k)\mathbf{x}(k-1) + \mathbf{w}(k) \tag{13}$$

where $\mathbf{x}(j)$ is the state of interest at time j, $\mathbf{F}(k)$ is the state transition matrix from time $k-1$ to time k, and where $\mathbf{w}(k) \sim N(0, \mathbf{Q}(k))$ is the associated process noise modelled as an uncorrelated white sequence with $E[\mathbf{w}(i)\mathbf{w}^T(j)] = \delta_{ij}\mathbf{Q}(i)$. The system is observed according to the linear measurement equation

$$\mathbf{z}(k) = H(k)\mathbf{x}(k) + \mathbf{v}(k) \tag{14}$$

where $\mathbf{z}(k)$ is the vector of observations made at time k, $H(k)$ the observation matrix, and where $\mathbf{v}(k) \sim N(0, \mathbf{R}(k))$ is the associated observation noise modelled as an uncorrelated white sequence with $E[\mathbf{v}(i)\mathbf{v}^T(j)] = \delta_{ij}\mathbf{R}(i)$. It is also necessary for $E[\mathbf{v}(i)\mathbf{w}^T(j)] = 0$.

From the above assumption the linear Kalman filter can be derived[1]. Adopting the information formulation introduced previously an alternative form of the Kalman filter, known as the information filter[8], can be obtained. Define the information-state vector

$$\mathbf{Y}(k) \triangleq \mathbf{P}^{-1}(k)\mathbf{x}(k)$$

where $\mathbf{P}(k)$ is the covariance matrix of $\mathbf{x}$ at time step k, and the information matrix

$$\mathbf{I}(k) \triangleq \mathbf{P}^{-1}(k),$$

we can obtain the information filter update equations as follows:

$$\begin{aligned} \mathbf{I}(k) &= \mathbf{I}(k-1) + H^T(k)\mathbf{R}^{-1}(k)H(k) && (15) \\ \mathbf{Y}(k) &= \mathbf{Y}(k-1) + H^T(k)\mathbf{R}^{-1}(k)\mathbf{z}(k) && (16) \end{aligned}$$

4.2 Distributed Information Filtering

Applying the information form to the decentralized Kalman filter algorithm[9] we can obtain the decentralized information filter.

Consider the distributed system described in Section 1, at each time step k the stacked observation is denoted by

$$\bar{\mathbf{z}}(k) = [\mathbf{z}_1^T(k), \cdots, \mathbf{z}_N^T(k)]^T. \tag{17}$$

Partition the observation matrix and the observation noise vector corresponding to the observations as follows

$$\begin{aligned} H(k) &= [H_1^T(k), \cdots, H_N^T(k)]^T && (18) \\ \mathbf{v}(k) &= [\mathbf{v}_1^T(k), \cdots, \mathbf{v}_N^T(k)]^T. && (19) \end{aligned}$$

It is assumed that the observation noise partitions are uncorrelated

$$E[\mathbf{v}(k)\mathbf{v}^T(k)] = R(k) = blockdiag\{R_1(k), \cdots, R_N(k)\} \tag{20}$$

The system now consists of N equations in the form

$$\mathbf{z}_j(k) = H_j(k)\mathbf{x}(k) + \mathbf{v}_j(k) \tag{21}$$

with

$$E[\mathbf{v}_p(i)\mathbf{v}_q^T(j)] = \delta_{ij}\delta pq R_p(i). \tag{22}$$

Defining

$$\hat{\mathbf{Y}}_j(k) \triangleq H_j^T(k)R_j^{-1}(k)\mathbf{z}_j(k) \tag{23}$$

as the information-state contribution from observation $Z_j(k)$ and

$$\hat{\mathbf{I}}_j(k) \triangleq H_j^T(k)R_j^{-1}(k)H_j(k) \tag{24}$$

The information-state and information matrix update equations are therefore

$$\begin{aligned} \mathbf{Y}(k) &= \mathbf{Y}(k-1) + \sum_{j=1}^{N} \hat{\mathbf{Y}}_j(k) && (25) \\ \mathbf{I}(k) &= \mathbf{I}(k-1) + \sum_{j=1}^{N} \hat{\mathbf{I}}_j(k) && (26) \end{aligned}$$

In a decentralized system where no central fusion and control is provided, each node obtains the optimal estimation by assimilating information from all the other node. From the information update equation it can be seen that the information provided by each node depends on the configuration (the measurement model $H_j(k)$), and the relative accuracy of the sensors ($R_j(k)$). It is therefore necessary to coordinate the inter-nodal communication of observation information when the communication bandwidth and network topology prevent complete and speedy inter-nodal communication.

With proper measure of information, we are now ready to address the problem of coordinating communication in distributed sensor system using the team theoretic approach introduced in Section 2.

5 Coordinating Communication of Information

In the previous sections we have shown that in order for each node in a distributed system to obtain a global optimal estimation it is necessary to assimilate information from all other node. We have also introduced a measure for the quantity of information contained in observations. In the following we shall present an algorithm for coordination of communication in a distributed sensing system.

5.1 A General Framework

Let $\mathbf{x}(k)$ represent the state of the world at time k. Each node makes an observation with measurement model $H_i(k)$ and measurement noise covariance $R_i(k)$. The information $I_i(k)$ contained in the measurement is therefore $H_i^T(k)R^{-1}(k)H_i(k)$. However the information is in a matrix form. In order to compare information with different dimensions we define a scalar $i_i(k)$, or the **absolute information**, as the trace of the information matrix. Hence

$$i_i(k) \triangleq trace(\mathbf{I}_i(k)) \triangleq trace(H_i^T(k)\mathbf{R}^{-1}(k)H_i(k)). \quad (27)$$

Each node makes a decision $\mathbf{u}_i$ on how much information from other nodes are to be assimilated. Note that this decision is made based only on each node's local observations. Further specification of the set of decision strategies must be specified to satisfy the requirement of a well-defined loss function (see Section 2). For example, each node can decide whether assimilation of information is required at that node by comparing the information contained in its local observation with certain threshold value:

$$\mathbf{u}_i = \begin{cases} \textit{assimilation required}, & \textit{if } i_i(k) < i_{thresh} \\ \textit{no assimilation needed}, & \textit{if } i_i(k) > i_{thresh} \end{cases}$$

Next we define the team utility as the throughput of information within the network. The throughput L is defined as the sum of the total information being assimilated within the network. It is obvious that the throughput is a function of all the local decisions and the state of the world:

$$L = l(\mathbf{u}_1, \cdots, \mathbf{u}_N, \mathbf{x}).$$

The aim is to find a set of decision rules $\mathbf{u}_1, \cdots, \mathbf{u}_N$ so that L is maximized. In the case of no communication costs and constraints the optimal local decision rule is to always communicate. However there exists a limitation on the communication bandwidth and topological constraints. In general these constraints can be represented as a vector function of local decisions:

$$C(\mathbf{u}_1, \cdots, \mathbf{u}_N) = 0 \quad (28)$$

Finally the coordination of communication in distributed system is transformed into a constrained optimization problem. Methods such as the Lagrange multiplier and the Penalty function methods[2, 13] methods can be used. In general the above optimization is still a functional optimization problem which is hard to solve. Next we shall use an example to illustrate the the concept of communication coordination when resources are limited.

5.2 An Example: Surveilance

Considering a surveilance system consists of four independent tracking cameras monitoring an area which is divided into four sectors each of which is associated with a tracking camera. All cameras can monitor the whole area, but the accuracy of the observations differs depending on whether the target is inside the sector which belongs to that camera. Each camera independently decides on whether to assimilate information from other cameras or not[2]. The overall communication capacity is limited.

[2]Other strategies are possible, for example, the camera independently decide whether to assimilate information from one, two or all other cameras

In this case it is assumed that there is a limit on how many assimilations which can be made at a time. This simplification is justified since each assimilation requires the communication of the information state vector and the information matrix, which are of the same sizes for all cameras. The problem is therefore to decide the communication strategy for each camera. In this case there are four decision pairs for each camera: target in own sector and communicate; target in other sector and communicate; target in own sector and not communicate; target in other sector and not communicate. Note that whether the target is in own sector or not is a local observations. The real location of the target and individual observations are correlated and this correlation must be known in advance before the expected team utility (overall information flow) can be calculated.

Let us number the sectors of the monitored area as 1,2,3 and 4. Denoting the location of the target as $\mathbf{x}$ so $\mathbf{x} = \{1, 2, 3, 4\}$. The decision variables $\mathbf{u}_i, i = 1, \cdots, 4$ is the permutation of communicate/not communicate and target in own sector/target in other sector. The utility is calculated as the sum of the assimilated information. The information is computed from Equation 24 in section 4. Assuming the measurement matrix is an identity matrix, i.e. $H = I$, and the variance of the observation noise R when the target is in the other sector is twice as high as that when the target is in its own sector. The information can be calculated from Equation 27.

Before this can be done we must obtain the joint probability of the random variable $\mathbf{x}$ (the state of the world) and the observations made by each camera. Assuming the target is equally likely to appear in each of these sectors, the probability of all cameras agreeing and partially agreeing is shown in Table 3. The constraint imposed by the communication capacity in the network is described as the total number of assimilations allowed within the network. This constraint will reduce the total number of possible decision permutations. By enumerating the decision permutations it is not difficult to find the decision strategy which will give maximum information throughput in the network.

$\mathbf{x} = i$	Number of cameras correctly identifying target in sector i				
$\mathbf{z}$	4	3	2	1	0
Prob.	0.5	0.3	0.1	0.07	0.03

Table 3: Joint probability distribution of the state $\mathbf{x}$ and local observations

6 Discussions and Future Work

The decentralized estimation and control problem has often been addressed separately in the literature[14]. In reality communication constraints which exist in the distributed network mean that it is essential to coordinate the communication in order to achieve best estimation results while satisfying those constraints. Team theory has been found useful in addressing the above problem although many questions are still unanswered:

- The functional optimization problem doesn't have a solution in general. Only finite number of decision rules are allowed in the examples presented in this paper.
- In general the communication coordination problem is a multi-stage decision making problem. In the case of limited horizon and finite decision rules it is straightforward to apply the stochastic dynamic programming algorithms since both methods can be regarded as to maximizing some global expected utility function[3].
- By not assimilating information from all the nodes, the global optimality condition of the decentralized information filter is violated. This problem is equivalent to that of the asynchronous communication problem[9].

Future work include the extension of the basic team theory as well as implementation to non-trivial systems. This includes:

- Applying mixed strategies instead of the finite strategies by associating probability to each decision rules.
- Applying the team theory to solve the communication coordination problems in multi-sensor robot system.

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8 References

[1] Y. Bar-Shalom and T.E. Fortmann. *Tracking and Data Association.* Academic Press, 1988.

[2] T. Butler and A. V. Martin. On a method of courant for minimizing functionals. *J. of Math. Phys.*, 41:291–299, 1962.

[3] D. E. Catlin. *Estimation, Control, and the Discrete Kalman Filter.* Springer-Verlag, 1989.

[4] T. M. Cover and J. A. Thomas. *Elements of Information Theory.* John Wiley and Sons, 1991.

[5] E. H. Durfee, V. R. Lesser, and D Corkill. *Distributed Artificial Intelligence*, chapter Cooperation Through Communication in a Distributed Problem Solving Network, pages 29–58. Morgan Kaufmann Publishers, 1987.

[6] Y. C. Ho. Team decision theory and information structures. *Proceedings of the IEEE*, 68(6):644–654, 1980.

[7] J. Marshak and R Radnor. *The Economic Theory of Teams.* Yale University Press, 1972.

[8] P. Maybeck. *Stochatic Models, Estimation, and Control*, volume 1. Academic Press, 1979.

[9] B. Rao. *A Fully Decentralised Multi-sensor System for Tracking and Surveilance.* PhD thesis, University of Oxford, 1991.

[10] C. Shannon. A mathematical theory of communication. *Bell Systems Technical Journal*, 27:379–423, 1948.

[11] R. G. Smith and R. Davis. Frameworks for cooperation in distributed problem solving. *IEEE Transactions on Systems, Man and Cybernetics*, 11(1):61–70, 1981.

[12] J. Von Neumann and O. Morgenstein. *Theory of Games and Economic Behaviour.* Princeton University Press, 1947.

[13] W. Wen. *Multi-sensor Geometric Estimation.* PhD thesis, University of Oxford, 1992.

[14] H. S. Witsenhausen. Separation of estimation and control for discrete time systems. *Proccedings of the IEEE*, 59(11):1557–1566, 1971.

[3]In the case of stochastic dynamic programming the integrated utility is maximized