Social Influence Modeling for Utility Functions in Model Predictive Control

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Abstract

Social influence has no small effect on the preferences and behavior of agents in a social space. Contrary to rationality, we sometimes compromise our own needs for those of others. Thus, social influence has important implications in agent cognitive modeling for multi-objective decision-making problems. Namely, where these activities occur within a social context, the intentional preferences or utility of an agent may be subsumed, to a greater or lesser degree, by the influences of other agents. In this paper, a socially-aware model predictive controller is proposed using a social influence network theory and applied to a HVAC control problem. It transforms individual agent utility to socially-influenced utility reflecting interagent influences due to their existing relationships.

Introduction

Social influence has no small effect on the preferences and behavior of individuals in a social space. Contrary to the principle of rationality, we sometimes compromise our own needs for those of others. Thus, social influence has important implications in agent cognitive modeling for multi-objective decision-making problems. Specifically, where decision-making occurs within a social context, the intentional preferences or utility of an agent may be subsumed, to a greater or lesser degree, by the influences of other agents (Friedkin 1998). Further, where individual subsumption happens among a close-knit group of agents, a centrality (a measure of importance based on the structure of the network) related to the quality of its relationships will be evident. In short, an agent will alter its preferences about the social space to favor the agents that are important to it.

This paper introduces a model of interagent social influences for a model predictive controller for a shared space reflecting the result of those influences. In effect, the controller transforms the individual agent utilities using a transformation with explicit parameters for *susceptibility* and *roles*. This model of social relationships is based on a mathematical model of consensus formation within a social influence network theory (Friedkin 1998).

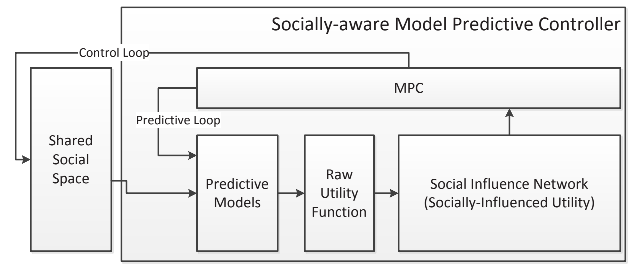


Figure 1: Overview of the controller

This controller is illustrated in Figure 1 where the conditions of the shared space are input to the utility of the agents. In turn, this social influence network transforms each agent's *raw utility* into a *socially-influenced utility*. A model predictive controller then determines the best control decision to make based on that transformed utility.

This transformation is effected by the interagent influence matrix. We set two parameters for each agent: *susceptibility* and *role multipliers*. While susceptibility is the degree to which an agent is willing to compromise, role multipliers allow the agent to assign influence to specific roles.

We show that the consensus formation equations of Friedkin's social influence theory are suitable to transform individual utility for used in a model predictive controller. Specifically, we demonstrate that the utility of the individual with the highest centrality dominates those of others.

To demonstrate the approach, we present the results of simulations wherein a socially-aware model predictive controller is used in a multi-objective decision-making process. Stemming from research in intelligent environments (Mozer, Vidmar, and Dodier 1997), these simulations approximate a residential home using a comfort-based predictive controller for its HVAC system. An occupying agent's utility provides input to the socially-aware controller which, in turn, makes a control decision that modifies the thermal conditions inside the home. The centrality of one agent (considered in the dependent role) is varied by changing its parameters.

Note that the controller's goal is to optimize transformed utility. There is no guarantee of optimization of the underlying utilities. Individual agents may compromise their preferences for the preferences of other agents.

Background

Social influence network theory

Social influence network theory contains a formula for the formation of consensus that ”describes a process in which a group of actors weigh and integrate the conflicting influences of significant others - within the context of social structural constraints” (Friedkin 1998). This is a form of compromise where an agent's opinion is influenced by the opinions of other agents. We take the view here that opinions are analogous to utility and can be represented by scalar numbers as follows:

Let N agents share a space. Let $X = [x_{ik}]$ be an $N \times K$ matrix of the exogenous factors of that space that influence the agents. Let $B = [b_{km}]$ be a $K \times M$ matrix of coefficients. In essence, if X are the conditions of the shared space from which an agent derives its utility, B is the set of weights placed on those conditions. $Y^{(t)} = [y_{im}^{(t)}]$ is an $N \times M$ matrix of M-dimensional preferences for N agents at time t. The initial (at time 1) and influenced preferences at time t can then expressed as:

$$Y^{(1)} = XB \tag{1}$$

$$Y^{(t)} = AWY^{(t-1)} + (I - A)Y^{(1)} \tag{2}$$

Here, Equation (2) describes the subsequent transformation of those opinions over time where $A = [a_{ii}]$ is a diagonal weight matrix indicating the influence coefficient of each agent, i, and $W = [w_{ij}]$ is the weight matrix $N \times N$ describing the influences of the agents on each other. The weight w_{ij} indicates the influence of agent j on agent i. Equations (3) and (4) constrain the weight matrix, while Equation (5) describes a compromise relationship.

$$0 \leq w_{ij} \leq 1 \tag{3}$$

$$\sum_j w_{ij} = 1 \tag{4}$$

$$w_{ii} = 1 - a_{ii} \tag{5}$$

The first term of Equation (2) forms the norm of the group. The revised opinion is the weighted sum of the norm at that timestep and the agent's initial opinion represented by the second term. These relative weights are determined by the coefficient of the social influence for each agent, a_{ii}. Thus, each agent's own opinion is accorded some weight at this level, though its opinion is also accounted for in the norm.

Thermal comfort and control

The primary goal of HVAC (Heating, Ventilating and Air Conditioning) is to create an environment that is comfortable for its occupants. Thermal comfort is studied in psychology as an attempt to understand individual occupant responses to the physical environment. When considering a thermal comfort neutrality as the physiological state where heat generation and heat dissipation are equal, a thermal comfort response is then seen as the psychological response to deviation around that state. How this is measured is still an active research topic, but a standard is readily available in the engineering field.

Notably, the prevalent standard measure of thermal comfort is the ASHRAE-scale based on a Predicted Mean Vote (PMV) (ASHRAE 2004). The PMV indicates the expected thermal comfort sensation of a large group of people on a scale ranging from -3 to +3 reflecting sensations of cold and hot, respectively. A neutral thermal comfort score on this scale (PMV = 0) is from a combination of environmental and individual factors for which no change is desired. The factors contributing to the comfort response of the individual are given as four environmental variables (relative humidity, mean radiant temperature, ambient air temperature,air velocity) and two personal variables (metabolic rate and clothing levels). This is discussed briefly in (Liang and Du 2005) and a full treatment may be found in (ASHRAE 2004; Fanger 1970).

Model predictive control

The term model-based predictive control (MPC) refers to a range of strategies designed to optimize a control policy by maximizing some utility function. These strategies can be summarized by three components. These are the prediction model, the objective function and the process of obtaining the control law (Camacho and Bordons 2004).

(Mozer, Vidmar, and Dodier 1997) describes a model predictive controller which forms the objective function in terms of occupant discomfort and an energy cost both measured in dollars:

$$\bar{J}_u = \sum_{t=t_0+1}^{t_0+k} e(u_t) + \bar{m}_u(x_t) \tag{6}$$

where e is the energy cost and m is the ”misery” of the occupants in dollars. These are described by their respective, underlying models. The model predictive controller then makes predictions about all the possible control policies over a receding, finite window of time. Executing the first control decision, the models are updated and the cycle repeated.

At each time step in a discrete control scenario, the optimal control policy is found by maximizing a utility function informed by prediction models over a finite-horizon. The first control action is then executed, the models updated, and the optimal policy recalculated.

Driven by industry, the application of MPC controllers is found to be used in a number of areas dominated by manufacturing process control (Qin and Badgwell 1997). However, given the simplicity of the approach, it is suitable for other scenarios such as HVAC control. Indeed, the use of an MPC controller for HVAC control is also shown in (Mozer, Vidmar, and Dodier 1997; Freire, Oliveira, and Mendes 2008; Hamdi and Lachiver 1998; Lei, Hongli, and Cai 2006). Notably, Friere (Freire, Oliveira, and Mendes 2008) investigates the use of PMV as a cost function in the HVAC control scenario. Also, (Mozer, Vidmar, and Dodier 1997; Freire, Oliveira, and Mendes 2008) investigate optimization of both thermal comfort and energy cost generally using MPC.

Methodology

Problem formulation

(Mozer, Vidmar, and Dodier 1997) formulated an HVAC control problem as a balance between an optimal setpoint and energy cost. In contrast, the problem is devised here as a set of divergent objectives combined into a consensus decision reflecting the effect of social influence. These objectives are individually modeled as the utility of each agent and combined using an influence network. This section describes modifications to Friedkin's consensus formation as it is included into a model predictive controller.

Socially-aware Model Predictive Controller

The basic model predictive controller is modified by changing the model of agent utility. Specifically, raw utility is transformed into socially-influenced utility according to Equation (8). The agent entity can be generalized as any entity that 1) shares the social space, 2) is impacted by control decisions on that space, 3) has some utility related to the state of that space. While this obviously may include people, this definition allows us to include other agents such as HVAC equipment. For example, an air conditioner is impacted by control decisions in that such decisions may cause the device to consume energy. Energy usage could then be considered as the utility function for that agent. In contrast to (Mozer, Vidmar, and Dodier 1997), the aggregate objective function can be simplified as a weighted sum of the utilities.

Social Space

The context for the control scenario is called the *social space*. Latané and Liu (Latané and Liu 1996) define social space as "an intersubjective matrix of psychological distances based on physical and social reality that provides a framework constraining how people are influenced by each other." In the example scenario of an HVAC control problem, the social space is defined by shared use of a physical location or environment (e.g. a residential home). It can also be defined by a shared fiscal responsibility for the energy use incurred by running the HVAC equipment.

Social agents

Social agents are those agents which jointly occupy a social space along one or more defining dimensions. In this work, agents have the following characteristics:

Occupancy An agent either occupies the social space at time t or it does not. In the HVAC problem, an agent away from the physical space at a given point in time will not be affected by any control decisions affecting the space in that time step. In Equation (8) below, occupancy is represented by a diagonal matrix $B^{(t)}$ where:

$$b_{ii}^{(t)} = \begin{cases} 1 & \text{agent } i \text{ occupies the space at time } t \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Susceptibility Susceptibility is defined in two ways. First, each agent may be more or less susceptible to the influences of the group norm. This is a form of compromise between one's own utility and the utility of other group members. It is defined here for the group of agents as the matrix A such that $0 < a_{ii} < 1$ and $a_{ij} = 0, i \neq j$.

Role multipliers Role multipliers are a convenient way to handle different classes of relationships. We assume that a relationship with one agent may be different than a relationship with another agent. It is also assumed that an agent's self-weight changes depending on some quality of the relationship. To simplify this, we assume that relationships fall into groups or roles. Each role then scales the effect each alter agent in that relationship role will have on the agent.

Role	Multiplier
peer	0.25
dependent	1.0
caregiver	0.25

Table 1: Sample Multiplier Settings

Agents represent each role as a scalar multiplier. Table 1 provides an example set of role multipliers. Theoretically, each agent could model roles individually. For the present, we assume that all agents use the same role multipliers.

Raw utility In this paper, a distinction is made between the *raw utility* of each agent and the *socially-influenced utility*. A raw utility function maps the conditions of the shared space to a set of preferences for a given agent. Here we denote the raw utility of the agents as vector $\vec{x}$ such that each agent's utility occupies the corresponding row's value.

Individual preferences are encoded into this characteristic. Any variances between individuals regarding utility based on the conditions of the shared space but independent of other agents occupying this space are therefore handled by the agent's raw utility function.

Socially-influenced utility Socially-influenced utility, on the other hand, represents the preferences of the individual when taking other agents into consideration.

To relate these to the mechanism from social influence network theory, the raw utilities of all the agents in a social space are considered as the initial opinion, x in Equation (1). We revise Wquations (1) and (2) to reflect the interrelated social influences for a single time-step. These equations are then combined into a single form by substituting $B\vec{x}$ for $Y^{(1)}$, because we assume that social influence is entirely internal to the agent. Therefore, the focus is on the relationships and each agent's internal cognition about its relationships.

$$Y' = AWB\vec{x} + (I - A)B\vec{x} \tag{8}$$

The influence network is represented by the weight matrix, W, according to the constraints given in (3), (4) and (5). As shown, this matrix can be used as a transformation function transforming a vector of individual utilities to a vector of utilities representing the effect of the influence of the relationships between the individual.

At each interval, the weight matrix W is updated. While *susceptibility* and *role multipliers* remain constant, the number of occupants of each role changes over time. W is

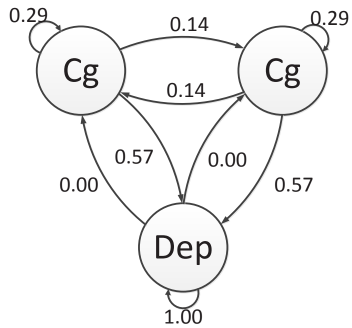


Figure 2: Influence Network

updated through the exponential function in Equation (9). Though any function could be used here we make the assumption that the rate at which self-weight changes is exponential in relation to the number of related agents in a given role and the quality of the relationship roles.

$$w_{ii} = e^{-k \sum_{u \in H}^{H} m_u n_u} \tag{9}$$

where H is a set of relationship roles. The function parameters are k, m and n, where m is a multiplier for each relationship role h and n is an N-dimensional vector describing the number of agents in relationship role h opposite agent i. The parameter k scales the effects of other agents globally. This represents the individual susceptibility of the agent to social influence. At $k = 1.0$, the agent is fully influenced by each individual term given in the sum. Agents that are not influenced by others have $k = 0$.

Once the self-weight is calculated, influence can then be distributed to the other agents. Equation (10) takes the remaining influence and distributes it according to their role.

$$w_{ij} = (1 - w_{ii}) \left(\frac{m_v}{\sum_{h \in H} m_h n_h} \right) \tag{10}$$

where v is the relationship role of agent j vis-a-vis agent i.

Example

Consider a network with three agents; two agents (1 and 2) are peers of each other and the other agent (3) is the dependent of the first two. This simulates two adults with a dependent child in the HVAC problem.

Assuming $k_1 = 1.0$, self-weight for agent 1 can be set as follows:

$$\begin{aligned} w_{11} &= e^{-1.0 \times ((1.0 \times 1) + (0.25 \times 1))} \\ &= 0.29 \end{aligned}$$

Given $(1 - w_{ii}) = \sum_{j \neq i} w_{ij}$, the remaining 0.71 is distributed to the other agents according to (10). This maintains the constraints given in (3), (4), (5). Assume the same weights for agent 2.

Let $k_3 = 0.0$ give the susceptibility for agent 3. Trivially, the self-weight for this agent will be 1.0 with none allocated to agents 1 and 2. This results in the weight matrix, W, in Table 2.

Agent	1	2	3
1	0.29	0.14	0.57
2	0.14	0.29	0.57
3	0.00	0.00	1.00

Table 2: Example Weight Matrix

Figure 2 illustrates the distribution of influence between the agents. The network centrality can be calculated as the sum of the weights on the outgoing influences. The caregiver agents (Cg) both have centrality of 0.43, while the dependent agent (Dep) has a centrality of 2.14. In effect, changes in the dependent agent's utility will have a larger influence on the aggregate utility.

Experiments

Model Predictive Control

In short, the outdoor space model provides the exogenous input for the system in terms of external weather conditions. The thermal space model then simulates the movement of heat through building walls resulting in an ambient indoor temperature. Utility functions for the individual agents then give a response to the temperature measured in terms of comfort (on a [0,1] scale). These are combined into a group utility as a weighted linear sum across all agents. The controller maximizes that utility over a finite horizon. The first control action of the optimal policy is implemented. Finally, the predictive models are updated and the next interval repeats the process.

Predictive Models The social space is conceptualized as a single-room having walls and ceiling with consistent thermal resistance/capacitance. It is represented as ambient indoor temperature with a heat transfer equation. As in (Mozer, Vidmar, and Dodier 1997), the transfer of heat through the walls is modeled by a first-order approximation. This is given by Equation (11).

$$\hat{h}_u(t) = \hat{h}_u(t-1) e^{\frac{-60\delta}{RC}} + (RQu(t) + g) \left(1 - e^{\frac{-60\delta}{RC}}\right) \tag{11}$$

This gives a prediction of the indoor temperature at time t. Parameters, R and C are respectively the resistance and capacitance factors. The equation is quantized by the interval size, δ. Finally, the current control decision (1 for heat, 0 for off, -1 for cool) is given by u while g is the outdoor temperature.

Occupancy is represented in the present work using a schedule-based model. For this report, each person agent was given a daily period of not occupying the physical space that randomly ranged between 4 and 12 hours.

Agent utility is represented differently based on agent type. This work distinguishes the agents as either person agents or thermal plant agents. Person agents are impacted by the effects of the thermal environment and provide utility in terms of thermal comfort. Thermal plant agents affect the thermal environment and provide utility in terms of energy usage. Both utilities are scaled to the [0,1] interval.

Thermal comfort utility is derived using fuzzy logic to map indoor temperature to a PMV score. This is a rough approximation of the method used in (Hamdi and Lachiver 1998) which provides a fast calculation of that score for online usage in HVAC controllers.

Data

To demonstrate the suitability of this approach to the MPC scenario, it suffices to show that the preferences of agents with greater weighted centrality dominate the social space. In this application, this means the more important an agent is (i.e. greater centrality), the more comfortable it is. To demonstrate, three simulations using different configurations of susceptibility were run. Each simulation consisted of thirty trials. Between each trial, the thermal comfort and occupancy profiles for each agent were varied randomly.

Common Configuration Parameters

Some parameters were commonly used across all configurations. Firstly, all simulations used three agents in a social network whose relationships are described by Table 3. Also, each agent used the role multipliers shown in Table 1. Finally, for all simulations, the dependent agent's susceptibility parameter is set to zero for all simulations.

Agent	1	2	3
1	self	peer	dependent
2	peer	self	dependent
3	caregiver	caregiver	self

Table 3: Agent Relationships

Each trial consists of 52,560 decision points (i.e. every 10 minutes for 12 months). At each decision point, external temperature was used as input and the following output was captured:

1. internal temperature
2. control decision (off, heat, cool)
3. agent's occupancy status
4. agent's raw utility
5. agent's influenced utility

Exogenous Data

External temperature data was provided by NOAA data files for Fayetteville, Arkansas (NOAA-NCDC 2011). Median temperature was $17.4°C$, minimum was $-13.0°C$ and the maximum was $43.0°C$.

Results

The section provides the daily mean values for each decision point index across all thirty trials.

Configuration 1

For configuration 1, the agents in the caregiver roles had susceptibility parameter set to 0.0 ($k = 0.0$). The recorded data is shown in Table 4 and Figure 3.

Agent	Mean Utility	Std Dev (-)	Std Dev (+)
1	0.11	0.06	0.01
2	0.10	0.04	0.02
3	0.07	0.02	0.02

Table 4: Configuration 1 results

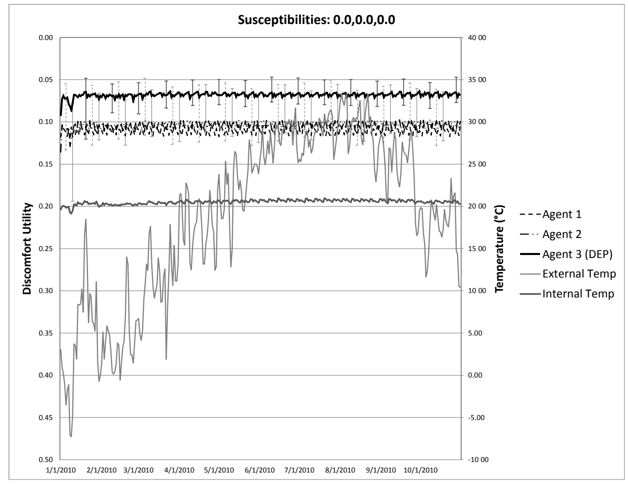


Figure 3: Simulation results for configuration 1

Configuration 2

For configuration 2, the agents in the caregiver roles had susceptibility parameter set to 0.5 ($k = 0.5$) while the dependent agent remained at $k = 0.0$. The recorded data is shown in Table 5 and Figure 4(a).

Agent	Mean Utility	Std Dev (-)	Std Dev (+)
1	0.04	0.02	0.02
2	0.07	0.03	0.01
3	0.04	0.02	0.01

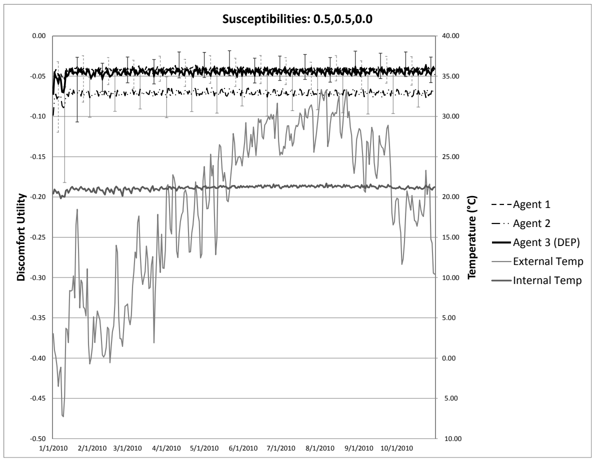
Table 5: Configuration 2 results

Configuration 3

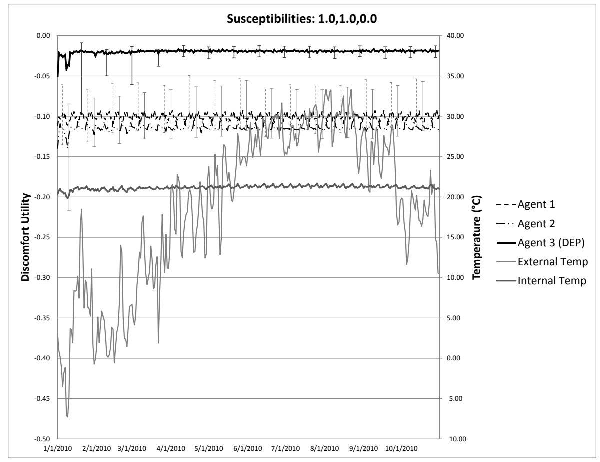
For configuration 3, the agents in the caregiver roles had susceptibility parameter set to 1.0 ($k = 1.0$) while the dependent agent remained at $k = 0.0$. The recorded data is shown in Table 6 and Figure 4(b).

Discussion

Importance in the social space is derived from the self-weight of the agent. We use the susceptibility parameter and role multipliers to set that weight. The results shown above indicate that as caregiver agent susceptibility increases, its centrality increases and therefore its utility decreases. Further, the daily averages increase for the dependent agent as the caregivers give more influence to it by increasing susceptibility.



(a) Configuration 2



(b) Configuration 3

Figure 4: Agent utility results for configurations 2 (a) and 3 (b)

Agent	Mean Utility	Std Dev (-)	Std Dev (+)
1	0.10	0.04	0.02
2	0.11	0.05	0.01
3	0.02	0.00	0.01

Table 6: Configuration 3 results

This work has focused on the framework for a HVAC scenario but it could be generalized to other control problems where a controller makes decisions on a shared, social space. Other such controllers include recommender systems for shared spaces such as media playlists.

Further, susceptibilities could be abstracted more to provide a robust and flexible system for parameterizing different susceptibilities to different exogenous inputs. In this way, the utility of each agent could be more thoroughly described in the formalisms presented in Friedkin's consensus formation, rather than outside the system. That is to say that an agent may also be more or less susceptible to the effects of the different dimensions of the social space. For this work, we assumed this susceptibility to be handled by the function generating the utility. However, this could also be handled by the matrix B by setting $0 < b_{ij} < 1$ accordingly.

Finally, this work provides a platform for learning the parameters from some form of feedback from the agents. Exploration of this goal would require extending the cognitive model of the agent in the simulator to provide appropriate feedback to the socially-aware controller. A full, human-based study would also serve the purpose.

Acknowledgments

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