Multi-Objective Route Planning Based on Machine Emotion

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Abstract: Nowadays, driverless technology is developing continuously, and route planning is a key link in driverless technology. To improve the intelligence of route planning, a multi-objective route planning approach based on machine emotion is proposed. The machine emotion adds human like emotion factors in the decision-making process. By combining with linear weighted multi-objective optimization, the human-computer interaction in navigation technology is improved. We used "OpenSceneGraph" software to simulate our method and made a field investigation. The experimental results show that this approach selects a route different from the ordinary one. The approach comprehensively considers the travel time, fuel consumption and passengers' emotions, which demonstrates the feasibility of our method.

Keywords: Driverless Technology, Machine Emotion, Route Planning, Artificial Emotion Simulation.

1. INTRODUCTION

With the improvement of economic strength and the continuous progress of scientific and technology, intelligent products gradually enter people's life, and people's expectations for intelligent products are also increasing, especially in the process of human–computer interaction of intelligent products. At the same time, intelligent vehicle technology has become a research hot issue in recent ten years, the reason is that intelligent vehicles can not only be used as a flexible weapon platform in the military. And in life, it is also a system that provides convenience and security for people [1]. With the recent emergence of artificial intelligence (AI) technology, autonomous vehicle industry has rapidly adopted this technology to investigate self-driving systems based on AI technology [2].

However, the current intelligent products can not interact with people emotionally, which requires intelligent products not only to identify people's emotions, but also to give feedback to the corresponding emotions. To make corresponding feedback on emotion, intelligent products are required to have a decision-making mode for emotion, and it is expected to simulate human emotion and express it.

At present, there are many artificial emotion models, including artificial emotion model based on rules and evaluation, emotion dimension theory, statistical learning, etc. Among them, the artificial emotion model based on emotion dimension theory is widely used.

The existing artificial emotion calculation analyzes the memory and external events by creating and updating the memory, using deep learning, establishing emotion transfer model and other technologies, so as to synthesize and express the machine emotion [3].

However, artificial emotion simulation should consider more aspects, including its current state, time input and environmental factors. Our research focus to creating a machine emotion to give intelligent products emotion which is similar to human being, and retain some of the characteristics of machine decision-making at the same time, making intelligent products more anthropomorphic in the process of human-computer interaction.

In navigation technology, the process of human-computer interaction is reflected in the users' input of origin and destination, and the navigation technology product outputs several feasible paths. However, the existing route can only be planned for a single goal such as distance or fuel consumption, and the passenger experience is not taken into account. To solve this problem, a multi-objective route planning strategy based on machine emotion is proposed.

Route planning algorithm is mainly divided into complete planning algorithm and sampling - based planning algorithm. The complete programming algorithms include breadth first pathfinding algorithm, Dijkstra algorithm, A^* algorithm, etc. The characteristic of this method is that if there is a path solution between the starting point and the target point then the solution must be obtained. Sampling based programming algorithms such as PRM algorithm and its variants, which are widely used in high dimensional programming problems.

On-road motion planning concerns about how to find a local trajectory that is free from collisions or violations of traffic laws, easy to be tracked by the low-level controllers, comfortable for the passengers, and consistent with the common practice of human drivers [4]. When people act in a familiar environment, the decision of path is usually different, which is related to their current emotion. For example, When people are anxious, they tend to choose the shortest time-consuming path.

However, they tend to choose a smooth and comfortable path when relaxed.

Our method of path planning strategy aims to simulate such emotion based decision-making, which can comprehensively optimize multiple objectives. By establishing machine emotion, the strategy results can integrate environmental information, current state and the emotion of vehicle passengers, resulting in a route that takes the optimization of multiple objectives and passenger emotion into account.

Avoiding rugged roads can not only optimize the mood, but also reduce the probability of accidents. Occupant safety remains one of the most challenging and significant design considerations in the automotive and transportation industry [5]. Our method can also improve the safety of passengers to a certain extent.

2. METHODOLOGY

2.1 Concept of Machine Emotion

Machine emotion refers to a simulated emotional state, which can affect decision-making according to the state of the machine itself, environmental factors and users' emotion.

Emotion originally refers to an attitude generated by human beings on whether objective things meet their own needs. It is a positive or negative attitude generated by human beings based on the environment and their own situation. A large number of studies show that people are not always completely rational, and emotion will affect the results of decision-making. If the emotional influence mechanism is added to the intelligent decision-making process, it is possible to find a more humanized solution. Machine emotion aims to give machines or intelligent products the same emotion as people, control and influence the decision-making process.

Our method adds a human like emotion influence mechanism to the path planning, so that the planning results will make users more satisfied.

2.1.1 Description of Machine Emotion

We use the dimension method to describe machine emotion. The expression of emotion dimension describes emotion on the continuously changing dimension, so an emotion can be expressed as a point in the multi-dimensional emotion space. Wundt first put forward the viewpoint of emotional dimension in 1986, holding that emotion is composed of three dimensions: pleasure-unhappiness, excitement-calm and tension-relaxation. In the field of emotional psychology, the PAD three-dimensional emotional space divides emotion into three dimensions: Pleasure-displeasure, Arousal-nonarousal, Dominance-submissiveness[6]. We use the PAD three-dimensional emotional space to describe machine emotion, as shown in Fig. 1. (0,0,0) indicates emotional calm.

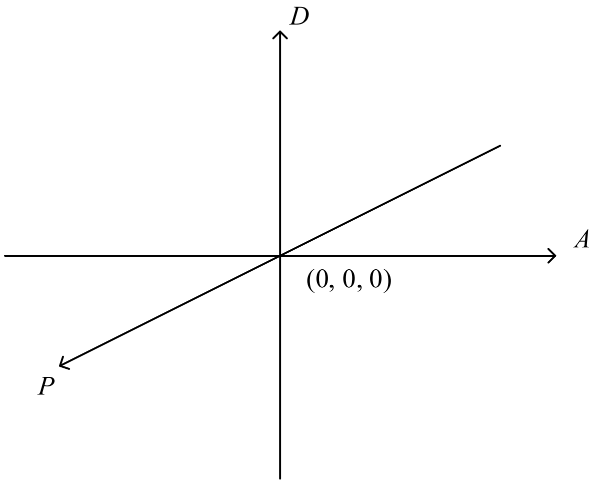

Fig. 1 PAD 3D emotional space

2.1.2. Transformation of Machine Emotion

People's own conditions and external events may promote emotion to change, but the input of external events is the most direct reason for the change. In the absence of external event input, machine emotion tends to flatten over time, which is expressed as gradually approaching the zero point in the three-dimensional emotion space. When an external event occurs, we define the external event as an emotion vector in three-dimensional space e_i, this vector acts on the current emotion E_0=(P_0, A_0, D_0), and lead to transformations of emotion. It is expressed as the change of point position in emotional space. Obviously, different external event inputs may have the same emotion vector. Similar to human emotion, when the current emotional state is different, for the same external event input, it may correspond to different emotion vectors.

Our method divide the path from the starting point to the end point into several sub paths of the same length, which are converted into an emotion vector according to the road conditions of each sub path.

Each sub path was evaluated by three indicators which constitute emotion vector $e_i = (r_i,\ t_i,\ g_i)$. e_i is defined as the emotion vector of segment i sub path. r_i , t_i and g_i are defined as road smoothness, estimated passing time, and energy costs of segment i sub path. Each indicator is quantified by a number in the range [-1, 1].

$$E = E_0 + \sum_{i=1}^{N} [e_i \times (\lambda_1, \lambda_2, \lambda_3)^{T}] = (P_t, A_t, D_t) \qquad (1)$$

where e_i is defined as an emotion vector, $(\lambda_1,\lambda_2,\lambda_3)^T$ is defined as the weight of three dimensions of emotion vector in different emotional states, which is determined by current emotion. N is the number of sub paths. We define the processed emotion vector as emotion transitional enabler. E_0 is defined as the machine emotion before the emotion conversion enabling effect, E is defined as the machine emotion after the emotion conversion enabling effect.

2.1.3 The influence of Current Emotion

Different current emotional states will have different reactions to the same event. For example, an anxious passenger's experience will be even worse when on the same crowded road.

$$\lambda_1 = \frac{|P_0|}{|P_0| + |A_0| + |D_0|} \tag{2}$$

$$\lambda_2 = \frac{|A_0|}{|P_0| + |A_0| + |D_0|} \tag{3}$$

$$\lambda_3 = \frac{|D_0|}{|P_0| + |A_0| + |D_0|} \tag{4}$$

2.1.4 Synthesis of Initial Machine Emotion

Before route planning, the machine emotion evaluation basis comes from the vehicle's evaluation of itself and the driver's emotional state. Here are some basic evaluation sources, as shown in Table 1.

Table 1 Initial emotion state

Emotion State	*P*	*A*	*D*
urgent	-0.95	-0.32	-0.63
not urgent	1.57	-0.79	0.38
pleasant	2.77	1.21	1.42
unpleasant	-1.60	-0.80	-2.00
Energy rich	1.72	1.71	0.22
Energy deficient	-1.20	0.40	-1.60

2.2 Multi-objective Route Planning Method

Our method introduces machine emotion into multi-objective optimization process. Applying this technology to vehicle navigation can solve the navigation problem of multi-objective optimization of driver's emotion, time, etc.

This method takes machine emotion as the optimization goal for route planning. The route planning method can comprehensively consume time, fuel consumption, road smoothness, road scenery, etc.

In the path planning process, multiple possible paths are found and divided into multiple sub paths, and a multi-objective function is established to predict the impact of each path on machine emotion. Our method will plan a path scheme to produce the best machine emotion.

2.2.1 Machine Emotion Objective Function

Our method maps out multiple possible route and establishes a multi-objective function aiming at the total fuel consumption and total driving time of the vehicle:

$$T_n = \sum_{\mathrm{i}=1}^{N} [t_{\mathrm{i}} \times p(N)] \tag{5}$$

$$G_n = \sum_{\mathrm{i}=1}^{N} [g_{\mathrm{i}} \times p(N)] \tag{6}$$

$$R_n = \sum_{\mathrm{i}=1}^{N} [r_i \times p(N)] \tag{7}$$

where T_n is defined as the total travel time of route *n*, G_n is defined as the total fuel consumption of route *n*, T_n is defined as the total travel time of route *n*. *R* is defined as the comfort level of the route. r_{i} , t_{i} and g_{i} are defined as road smoothness, estimated passing time, and energy costs of segment *i* sub path. N is defined as the number of divided sub paths. $p(N)$ is defined as penalty function for number of sub paths.

2.2.2 Machine Emotion Penalty Function

Our method introduce a penalty function into the established travel time and total fuel consumption model $p(N)$, the expression is

$$p(N) = \begin{cases} 1 \ , & N \leq 1.2 \times N_0 \\ \frac{N_0}{N} \times K, & N > 1.2 \times N_0 \end{cases} \tag{8}$$

where N is defined as the number of sub paths of current route, N_0 is defined as the number of sub paths of the shortest route. K is defined as the penalty coefficient with large value. When the route is converted into multiple sub paths, the number of sub paths will be larger when the distance of a path is longer because each sub path has the same length. If the number of sub paths is too large, a large penalty coefficient will be obtained, which will significantly increase the T_n , G_n and R_n, significantly increase the cost of passing through the route, and avoid detour in path selection. On the contrary, if the number of sub paths is within a reasonable range, it has no impact on the cost of passing through the route.

2.2.3 Linear Weighted Multi-objective Optimization Method Based on Machine Emotion

Among various algorithms for multi-objective optimization, linear weighting method is widely used. According to the importance of multiple objectives, the linear weighting method sets different weights for them, which is transformed into a single objective optimization problem.

$$\lambda_4 = \frac{|P_t|}{|P_t| + |A_t| + |D_t|} \tag{9}$$

$$\lambda_5 = \frac{|A_t|}{|P_t| + |A_t| + |D_t|} \tag{10}$$

$$\lambda_6 = \frac{|D_t|}{|P_t| + |A_t| + |D_t|} \tag{11}$$

$$C_n = \lambda_4 \times R + \lambda_5 \times T + \lambda_6 \times G \tag{12}$$

where C_n is defined as the total cost of passing route *n*. The disadvantage of linear weighting method is that it is difficult to determine the weight and can not guarantee the advantages and disadvantages of the results.

Our method can provide the weight judgment basis for the linear weighting method. The linear weighted multi-objective optimization algorithm based on machine emotion has a set of dynamic and personalized weight judgment methods, which can transform the multi-objective optimization into a single objective optimization problem for machine emotion. Among the multiple possible routes, the one with the least C_n is the target route.

This weight calculation based on our method can choose a route conducive to emotional recovery and help drivers and passengers keep calm.

2.2.4 Path Planning Process

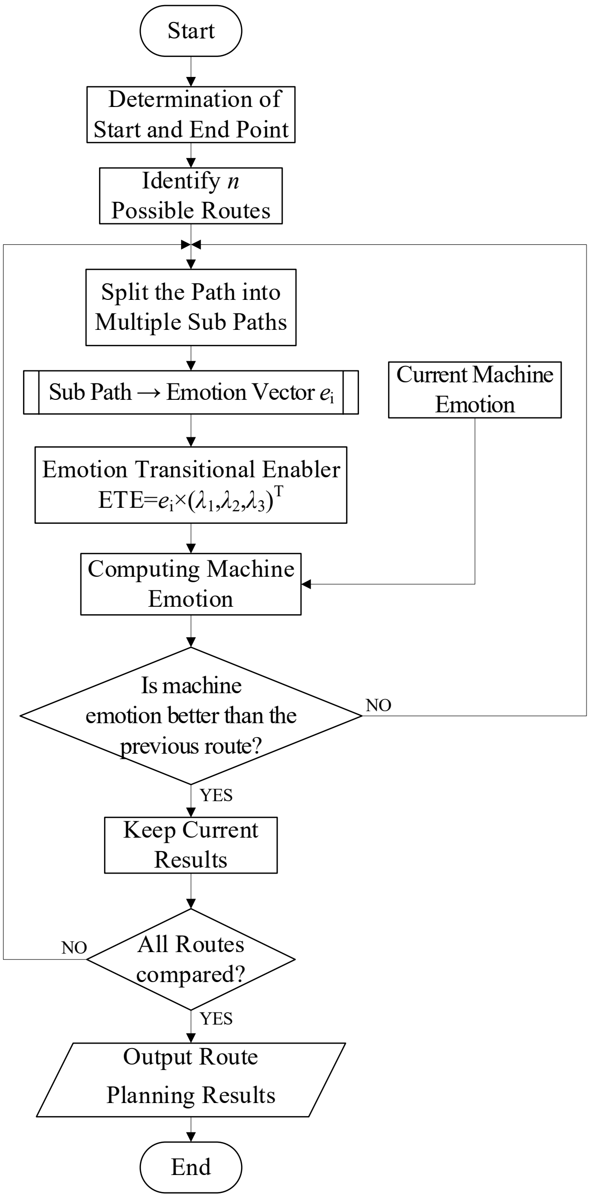

Fig. 2 Flowchart of path planning process

As shown in Fig. 2, after determining the starting point and end point, our method will first determine multiple feasible paths and divide the paths into multiple sub paths. The emotion vector generated by each sub path acts on the machine emotion. Compare the machine emotion step by step, select the path that can get the best machine emotion, and then determine the route planning results.

3. EXPERIMENT

To test our proposed method, the experiment was simulated in "OpenSceneGraph" on the computer of Windows 10 system.

Fig. 3 Simulation Route 1

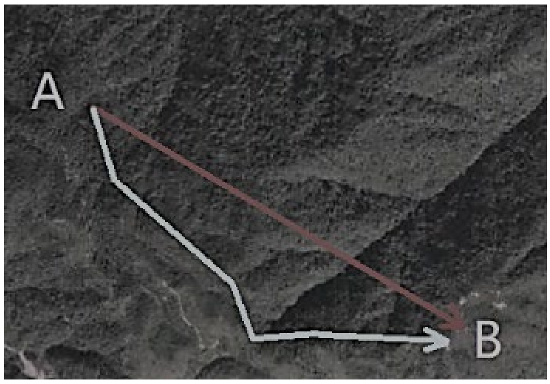

Fig. 4 Simulation Route 2

According to our method, the cost of passing the shortest route is higher. Therefore, the method described in this paper tends to choose a smoother path, as shown in Fig. 3 and Fig. 4. However, if choosing the shortest route, rough paths will be countered, which resulting in poor passenger experience and will lead to a bad mood.

To confirm the feasibility of this method, we conducted a field investigation. We had a practical experience on several urban paths with the same starting point and ending point. As shown in Fig. 5 and Fig. 6.

Fig. 5 Actual Route 1

Fig. 6 Actual Route 2

The experience results show that when passing through congested and rugged roads, the mood will become worse, resulting in reduced ride experience. The multi-objective route planning method based on machine emotion proposed in this paper can effectively avoid crowded and rugged sections and improve passengers' experience.

4. CONCLUSION

In this paper, a multi-objective path planning method based on machine emotion was proposed. To improve the process of human-computer interaction, we presented a method that takes machine emotion as the basis of route planning. Machine emotion comes from the current state, environmental factors and passengers' emotion. Using route planning method based on machine emotion, sections that may affect the mood of passengers were avoided. With experiments on "OpenSceneGraph" and field investigation, results indicate the feasibility of our method. However, our method relies on a large amount of road condition information.

Collective perception of connected vehicles can sufficiently increase the safety and reliability of autonomous driving by sharing perception information. However, collecting real experimental data for such scenarios is extremely expensive [7]. Among the hardware devices of many driverless vehicles, including cameras and on-board processors, driverless vehicles are realized by low-cost perception and high-performance computing [8]. The existence of a large number of on-board cameras makes it possible to obtain the road condition information required by the project in the future. Further research needs to be conducted to make the process of route planning easier and simpler in the future. There are areas that need to be improved in key technologies, human cognition, market rules, etc. And it still encounters problems and difficulties in different aspects [9]. The development of driverless vehicles will change driving into a complicated system, in which people, environment, and vehicles are closely integrated together to create a higher-efficient transportation service system [10]. It is hoped that our method of route planning will become the key link in the system.

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