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Dynamically Scaled Fuzzy Control of Autonomous Intelligent Actor

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Abstract

The article presents an approach toward the implementation of an Autonomous Intelligent Actor's (AIA) [1] fuzzy control mechanism, when each step of it is based on dynamically defined scale. Such a scale is directed by fuzzy conditional inference rule. The approach, offered in the article, allows "soft landing" of AIA on a Target even in a case of "unfriendly" docking situation.

Keywords

Fuzzy Logic, Fuzzy Control, Fuzzy Conditional Inference, AIA Orientation Principles

1. Introduction

The article introduces a multi-step fuzzy *control mechanism as* a "tactical" decision making process for *Intelligent Actor* (*AIA*) to approach a *Target*. For this purpose, we have proposed to use a set of dynamically defined scales for each *AIA* positioning coordinates. Such scales would reflect a "quasi" speed of *AIA* movement at each moment of time. For this purpose, we are using "human like behavior" approach toward an *AIA* control, namely "the further *AIA* from a *Target*, the faster *AIA* is moving (the larger steps *AIA* makes)" and "the closer *AIA* to a *Target*, the slower *AIA* moves (the smaller *AIA* steps)".

2. Logical Principles of AIA Orientation

2.1. Preliminary Considerations

Let consider that both Target and Object, a subject of mutual navigation, to be presented as octagons, depicted on Figure 1 [1]. Also, we use octagons for simplification's sake only. Given the fact that we are studying a *projection-based model*, both targets and objects could be presented as follows [1]:

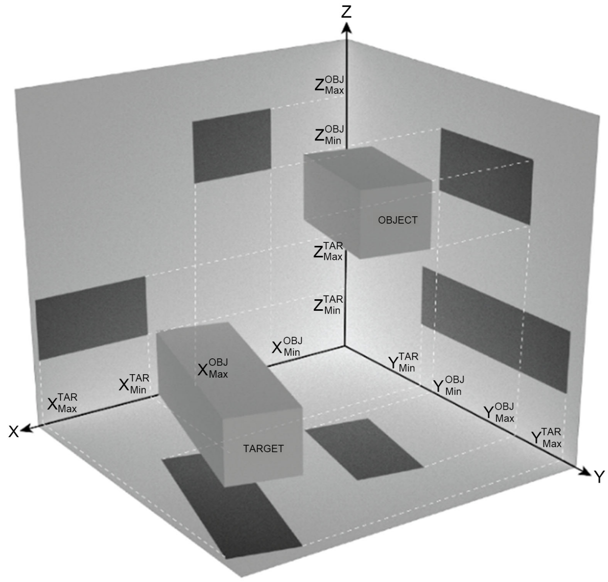

Figure 1. [1] Object and target space representation.

$T = \{t_j\}; j = \overline{1,n}$. Where *j* is number of heights of a Target, whereas $O = \{o_i\}; i = \overline{1,m}$ and *i* is number of heights of an Object. Both a target and an object could be presented in three-dimensional space as follows:

$$t_j \in T = \{x_j^t, y_j^t, z_j^t\}; j = \overline{1,n}, \; o_j \in O = \{x_i^o, y_i^o, z_i^o\}; i = \overline{1,m}. \tag{2.1}$$

On the other hand, from **Figure 1** each value of both a Target and an Object coordinate could be presented as a pair of minimal and maximal (per 3D coordinate) values of them. For targets, in particular

$$\begin{aligned}&\forall j \in [1,n] \,|\, x^T_{\min} = \min_j \{x_j^t\}, x^T_{\max} = \max_j \{x_j^t\}, y^T_{\min} = \min_j \{y_j^t\},\\ &y^T_{\max} = \max_j \{y_j^t\}, \min_j \{z_j^t\}, z^T_{\max} = \max_j \{z_j^t\}, z^T_{\min} = \min_j \{z_j^t\}\end{aligned} \tag{2.2}$$

By analogy, for objects we are getting:

$$\begin{aligned}&\forall j \in [1,n] \,|\, x^O_{\min} = \min_j \{x_j^o\}, x^O_{\max} = \max_j \{x_j^o\}, y^O_{\min} = \min_j \{y_j^o\},\\ &y^O_{\max} = \max_j \{y_j^o\}, \min_j \{z_j^o\}, z^O_{\max} = \max_j \{z_j^o\}, z^O_{\min} = \min_j \{z_j^o\}\end{aligned} \tag{2.3}$$

2.2. Predicates of Two Entities Mutual Relations

Considering (2.2)-(2.3) we can formulate some logical predicates, which would describe mutual positioning of two players in the paradigm of a *projection-based model*. Let us define predicates as relation symbols, describing a variety of positions of two entities in a space in a connection to each other.

2.3. Preconditions for Actions and Entity Shape Estimation

Before formulation of a possible actions, which could be performed by certain entities, and given (2.2) and (2.3) we have to consider for each entity the following points in 3-dimentional space $T_{center} = \{x^T_{center}, y^T_{center}, z^T_{center}\}$ for a Target and $O_{center} = \{x^O_{center}, y^O_{center}, z^O_{center}\}$ for an Object correspondingly, These points could define some conditional center of a gravity for each of them (median points in space)

$$x^{T}_{center}=\frac{x^{T}_{\max}+x^{T}_{\min}}{2},\quad x^{O}_{center}=\frac{x^{O}_{\max}+x^{O}_{\min}}{2} \tag{2.4}$$

$$y^{T}_{center}=\frac{y^{T}_{\max}+y^{T}_{\min}}{2},\quad y^{O}_{center}=\frac{y^{O}_{\max}+y^{O}_{\min}}{2} \tag{2.5}$$

$$z^{T}_{center}=\frac{z^{T}_{\max}+z^{T}_{\min}}{2},\quad z^{O}_{center}=\frac{z^{O}_{\max}+z^{O}_{\min}}{2} \tag{2.6}$$

2.4. Docking Positioning Predicates

We define the following predicates [2] by using (2.4)-(2.6)

1) Object *docks in front* of a Target (**DIF**)

$$DIF(O,T)\Rightarrow x^{T}_{center}=x^{O}_{center}\ \&\ z^{T}_{center}=z^{O}_{center}\ \&\ y^{T}_{\max}=y^{O}_{\min} \tag{2.7}$$

$$\Delta x=x^{T}_{center}-x^{O}_{center} \tag{2.8}$$

$$clX=\begin{cases}\left(x^{T}_{center}/x^{O}_{center}\right)*100, \Delta x\le 0,\\ \left(x^{O}_{center}/x^{T}_{center}\right)*100, \text{othervise}\end{cases} \tag{2.9}$$

$$\Delta y=y^{O}_{\min}-y^{T}_{\max} \tag{2.10}$$

$$clY=\begin{cases}\left(y^{O}_{\min}/y^{T}_{\max}\right)*100, \Delta y\le 0,\\ \left(y^{T}_{\max}/y^{O}_{\min}\right)*100, \text{othervise}\end{cases} \tag{2.11}$$

$$\Delta z=z^{T}_{center}-z^{O}_{center} \tag{2.12}$$

$$clZ=\begin{cases}\left(z^{T}_{center}/z^{O}_{center}\right)*100, \Delta z\le 0,\\ \left(z^{O}_{center}/z^{T}_{center}\right)*100, \text{othervise}\end{cases} \tag{2.13}$$

2) Object *docks at back* of a Target (**DAB**)

$$DAB(O,T)\Rightarrow x^{T}_{center}=x^{O}_{center}\ \&\ z^{T}_{center}=z^{O}_{center}\ \&\ y^{T}_{\min}=y^{O}_{\max} \tag{2.14}$$

$$\Delta x=x^{T}_{center}-x^{O}_{center} \tag{2.15}$$

$$clX=\begin{cases}\left(x^{T}_{center}/x^{O}_{center}\right)*100, \Delta x\le 0,\\ \left(x^{O}_{center}/x^{T}_{center}\right)*100, \text{othervise}\end{cases} \tag{2.16}$$

$$\Delta y=y^{O}_{\max}-y^{T}_{\min} \tag{2.17}$$

$$clY=\begin{cases}\left(y^{O}_{\max}/y^{T}_{\min}\right)*100, \Delta y\le 0,\\ \left(y^{T}_{\min}/y^{O}_{\max}\right)*100, \text{othervise}\end{cases} \tag{2.18}$$

$$\Delta z=z^{T}_{center}-z^{O}_{center} \tag{2.19}$$

$$clZ = \begin{cases} \left(z_{center}^{T} / z_{center}^{O}\right) * 100, \Delta z \le 0, \\ \left(z_{center}^{O} / z_{center}^{T}\right) * 100, \text{othervise} \end{cases} \tag{2.20}$$

3) Object *docks at left* of a Target (**DAL**)

$$DAL(O,T) \Rightarrow y_{center}^{T} = y_{center}^{O} \ \& \ z_{center}^{T} = z_{center}^{O} \ \& \ x_{\min}^{T} = x_{\max}^{O} \tag{2.21}$$

$$\Delta x = x_{\min}^{T} - x_{\max}^{O} \tag{2.22}$$

$$clX = \begin{cases} \left(x_{\max}^{O} / x_{\min}^{T}\right) * 100, \Delta x \le 0, \\ \left(x_{\min}^{T} / x_{\max}^{O}\right) * 100, \text{othervise} \end{cases} \tag{2.23}$$

$$\Delta y = y_{center}^{T} - y_{center}^{O} \tag{2.24}$$

$$clY = \begin{cases} \left(y_{center}^{T} / y_{center}^{O}\right) * 100, \Delta y \le 0, \\ \left(y_{center}^{O} / y_{center}^{T}\right) * 100, \text{othervise} \end{cases} \tag{2.25}$$

$$\Delta z = z_{center}^{T} - z_{center}^{O} \tag{2.26}$$

$$clZ = \begin{cases} \left(z_{center}^{T} / z_{center}^{O}\right) * 100, \Delta z \le 0, \\ \left(z_{center}^{O} / z_{center}^{T}\right) * 100, \text{othervise} \end{cases} \tag{2.27}$$

4) Object *docks at right* of a Target (**DAR**)

$$DAR(O,T) \Rightarrow y_{center}^{T} = y_{center}^{O} \ \& \ z_{center}^{T} = z_{center}^{O} \ \& \ x_{\max}^{T} = x_{\min}^{O} \tag{2.28}$$

$$\Delta x = x_{\max}^{T} - x_{\min}^{O} \tag{2.29}$$

$$clX = \begin{cases} \left(x_{\min}^{O} / x_{\max}^{T}\right) * 100, \Delta x \le 0, \\ \left(x_{\max}^{T} / x_{\min}^{O}\right) * 100, \text{othervise} \end{cases} \tag{2.30}$$

$$\Delta y = y_{center}^{T} - y_{center}^{O} \tag{2.31}$$

$$clY = \begin{cases} \left(y_{center}^{T} / y_{center}^{O}\right) * 100, \Delta y \le 0, \\ \left(y_{center}^{O} / y_{center}^{T}\right) * 100, \text{othervise} \end{cases} \tag{2.32}$$

$$\Delta z = z_{center}^{T} - z_{center}^{O} \tag{2.33}$$

$$clZ = \begin{cases} \left(z_{center}^{T} / z_{center}^{O}\right) * 100, \Delta z \le 0, \\ \left(z_{center}^{O} / z_{center}^{T}\right) * 100, \text{othervise} \end{cases} \tag{2.34}$$

5) Object *docks on top* of a Target (**DOT**)

$$DOT(O,T) \Rightarrow x_{center}^{T} = x_{center}^{O} \ \& \ y_{center}^{T} = y_{center}^{O} \ \& \ z_{\max}^{T} = z_{\min}^{O} \tag{2.35}$$

$$\Delta x = x_{center}^{T} - x_{center}^{O} \tag{2.36}$$

$$clX = \begin{cases} \left(x_{center}^{T} / x_{center}^{O}\right) * 100, \Delta x \le 0, \\ \left(x_{center}^{O} / x_{center}^{T}\right) * 100, \text{othervise} \end{cases} \quad (2.37)$$

$$\Delta y = y_{center}^{T} - y_{center}^{O} \quad (2.38)$$

$$clY = \begin{cases} \left(y_{center}^{T} / y_{center}^{O}\right) * 100, \Delta y \le 0, \\ \left(y_{center}^{O} / y_{center}^{T}\right) * 100, \text{othervise} \end{cases} \quad (2.39)$$

$$\Delta z = z_{\max}^{T} - z_{\min}^{O} \quad (2.40)$$

$$clZ = \begin{cases} \left(z_{\min}^{O} / z_{\max}^{T}\right) * 100, \Delta z \le 0, \\ \left(z_{\max}^{T} / z_{\min}^{O}\right) * 100, \text{othervise} \end{cases} \quad (2.41)$$

6) Object *docks under* (*at bottom*) of a Target (**DUN**)

$$DUN(O,T) \Rightarrow x_{center}^{T} = x_{center}^{O} \;\&\; y_{center}^{T} = y_{center}^{O} \;\&\; z_{\min}^{T} = z_{\max}^{O} \quad (2.42)$$

$$\Delta x = x_{center}^{T} - x_{center}^{O} \quad (2.43)$$

$$clX = \begin{cases} \left(x_{center}^{T} / x_{center}^{O}\right) * 100, \Delta x \le 0, \\ \left(x_{center}^{O} / x_{center}^{T}\right) * 100, \text{othervise} \end{cases} \quad (2.44)$$

$$\Delta y = y_{center}^{T} - y_{center}^{O} \quad (2.45)$$

$$clY = \begin{cases} \left(y_{center}^{T} / y_{center}^{O}\right) * 100, \Delta y \le 0, \\ \left(y_{center}^{O} / y_{center}^{T}\right) * 100, \text{othervise} \end{cases} \quad (2.46)$$

$$\Delta z = z_{\min}^{T} - z_{\max}^{O} \quad (2.47)$$

$$clZ = \begin{cases} \left(z_{\min}^{T} / z_{\max}^{O}\right) * 100, \Delta z \le 0, \\ \left(z_{\max}^{O} / z_{\min}^{T}\right) * 100, \text{othervise} \end{cases} \quad (2.48)$$

2.5. Fuzzification of Docking Positioning

We represent *clX* from (2.9), (2.16), (2.23), (2.30), (2.37), (2.44), and also *clY* from (2.11), (2.18), (2.25), (2.32), (2.39), (2.46) and *clZ* from (2.13), (2.20), (2.27), (2.34), (2.41), (2.48) as a *fuzzy set*, forming linguistic variable, described by a triplet of the form $CL = \left\{\left\langle cl_i, U_{cl}, \widetilde{CL}\right\rangle\right\}, cl_i \in T(u_{cl}), \forall i \in [0, CardU_{CL}]$, where $T_i(u_{cl})$ is extended term set of the linguistic variable "***Closeness***" from Table 1, $\widetilde{CL}$ is normal fuzzy set with correspondent membership function $\mu_{cl} : U_{CL} \to [0,1]$.

We will use the following mapping

$\alpha : \widetilde{CL} \to U_{CL} \mid u_{cl} = Ent\left[\left(CardU_{CL} - 1\right) \times cl_{norm}\right] \mid \forall i \in [0, CardU_{CL}]$, were

$$\widetilde{CL} = \int_{U_{cl}} \mu_{cl}(u_{cl}) / u_{cl} \quad (2.49)$$

Table 1. Linguistic variables for object/target closeness and control steps scale.

Value of variable		$\forall i, \forall j \in [0,10]$, $st_j \in U_{ST}$, $cl_i \in U_{CL}$
"*Closeness*"	"*Steps_scale*"	
smallest	smallest	0
almost smallest	almost smallest	1
small	small	2
bit higher than small	bit higher than small	3
almost average	almost average	4
average	average	5
bit higher than average	bit higher than average	6
pretty large	pretty large	7
large	large	8
almost largest	almost largest	9
largest	largest	10

On the other hand, similarly to the previous cases, to determine the estimates of the membership function in terms of singletons from (2.49) in the form $\mu_{cl_i}(cl_i)/cl_i \mid \forall i \in [0, CardU_{CL}]$ we propose the following procedure.

$$\forall i \in [0, CardU_{CL}], \mu_{cl}(cl_i) = 1 - \frac{1}{CardU_{CL} - 1} \times \left| i - Ent\left[(CardU_{CL} - 1) \times cl_{norm} \right] \right| \quad (2.50)$$

We also represent $\Delta x_\cdot$ from (2.8), (2.15), (2.22), (2.29), (2.36), (2.43) and also $\Delta y_\cdot$ from (2.10), (2.17), (2.24), (2.31), (2.38), (2.45) and finally $\Delta z_\cdot$ from (2.12), (2.19), (2.26), (2.33), (2.40), (2.47) as a *fuzzy set*, forming linguistic variable, described by a triplet of the form $ST = \{\langle st_j, U_{ST}, \widetilde{ST} \rangle\}, st_j \in T(u_{st}), \forall j \in [0, CardU_{ST}]$, where $T_j(u_{st})$ is extended term set of the linguistic variable "***Steps_scale***" from Table 1, $\widetilde{ST}$ is normal fuzzy set with correspondent membership function $\mu_{st} : U_{st}[0,1]$.

We will also use the following mapping

$\Omega : \widetilde{ST} \to U_{ST} \mid u_{st} = Ent\left[(CardU_{ST} - 1) \times st_j \right] \mid \forall j \in [0, CardU_{ST}]$, were

$$\widetilde{ST} = \int_{U_{ST}} \mu_{st}(u_{st})/u_{st}. \quad (2.51)$$

On the other hand, similarly to the previous cases, to determine the estimates of the membership function in terms of singletons from (2.51) in the form $\mu_{st_j}(st_j)/st_j \mid \forall j \in [0, CardU_{ST}]$ we propose the following procedure.

$$\forall j \in [0, CardU_{ST}], \mu_{st_j}(st_j) = 1 - \frac{1}{CardU_{ST} - 1} \times \left| j - Ent\left[(CardU_{ST} - 1) \times st_j \right] \right| \quad (2.52)$$

To convert (2.49)-(2.52) into fuzzy logic-based statement and terms from Table 1 *we use* a *Fuzzy Conditional Inference Rule*, formulated by means of "*common sense*" as a following conditional clause:

$$P = \text{"IF } (\widetilde{CL} \text{ is } CL), \text{ THEN } (\widetilde{ST} \text{ is } ST)\text{"} \quad (2.53)$$

In other words, we use fuzzy conditional inference of the following type [3] [4]

[5] [6]:

Ant 1: If ***Closeness*** is *CL* then ***Steps_scale*** *is ST*

Ant2: ***Closeness*** is *CL'*

-- (2.54)

Cons: ***Steps_scale*** is *ST'*.

Where $CL, CL' \subseteq U_{CL}$ and $ST, ST' \subseteq U_{ST}$.

Note that statement (2.54) represents "modus-ponens" syllogism. Given that we use the following type of implication [7]

$$A \to B = \begin{cases} (1-a)\cdot b, a > b, \\ 1, a \le b \end{cases} \tag{2.55}$$

Now for fuzzy sets (2.49) and (2.51) a *binary relationship* for the fuzzy conditional proposition for fuzzy logic with implication of type (2.55) is defined as

$$\begin{aligned} &R\left(A_1(cl), A_2(st)\right) = CL \times U_{CL} \\ &\to ST \times U_{ST} = \int_{U_{CL}\times U_{ST}} \left(\mu_{cl}(u_{cl})/u_{cl} \to \mu_{st}(u_{st})/u_{st}\right)/(u_{cl}, u_{st}) \end{aligned} \tag{2.56}$$

and since we consider that $CardU_{CL} = CardU_{ST}$, then expression (2.56) looks like

$$\mu_{cl}(u_{cl})/u_{cl} \to \mu_{st}(u_{st})/u_{st} = \begin{cases} \left(1-\mu_{cl}(u_{cl})\right)\cdot \mu_{st}(u_{st}), \mu_{cl}(u_{cl}) > \mu_{st}(u_{st}), \\ 1, \mu_{cl}(u_{cl}) \le \mu_{st}(u_{st}). \end{cases} \tag{2.57}$$

By using (2.54) and given a *unary relationship* $R\left(A_1(cl')\right) = CL'$ one can obtain the consequence $R\left(A_2(st')\right)$ by compositional rule of inference (CRI) to $R\left(A_1(cl')\right)$ and $R\left(A_1(cl), A_2(st)\right)$ of type (2.57):

$$\begin{aligned} &R\left(A_2(st')\right) = CL' \circ R\left(A_1(cl), A_2(st)\right) \\ &= \int_{U_{CL}} \mu_{cl'}(u_{cl})/u_{cl} \circ \int_{U_{CL}\times U_{ST}} \mu_{cl}(u_{cl}) \to \mu_{st}(u_{st})/(u_{cl}, u_{st}) \\ &= \int_{U_{ST}} \bigcup_{cl \in U_{cl}} \left(\left[\mu_{cl'}(u_{cl}) \wedge \mu_{cl}(u_{cl})\right] \to \mu_{st}(u_{st})\right)/u_{st}. \end{aligned} \tag{2.58}$$

But for practical purposes we will use another *Fuzzy Conditional Rule* (*FCR*)

$$\begin{aligned} &R\left(A_1(cl), A_2(st)\right) = \left(CL \times U_{CL} \to ST \times U_{ST}\right) \cap \left(\neg CL \times U_{CL} \to U_{ST} \times \neg ST\right) \\ &= \int_{U_{CL}\times U_{ST}} \left(\mu_{cl}(u_{cl}) \to \mu_{st}(u_{st})\right) \wedge \left(\left(1-\mu_{cl}(u_{cl})\right) \to \left(1-\mu_{st}(u_{st})\right)\right)/(u_{cl}, u_{st}) \end{aligned} \tag{2.59}$$

Given (2.57) from (2.59) we are getting

$$\begin{aligned} &R\left(A_1(cl), A_2(st)\right) \\ &= \left(\mu_{cl}(u_{cl}) \to \mu_{st}(u_{st})\right) \wedge \left(\left(1-\mu_{cl}(u_{cl})\right) \to \left(1-\mu_{st}(u_{st})\right)\right) \\ &= \begin{cases} \left(1-\mu_{cl}(u_{cl})\right)\cdot \mu_{st}(u_{st}), \mu_{cl}(u_{cl}) > \mu_{st}(u_{st}), \\ 1, \mu_{cl}(u_{cl}) = \mu_{st}(u_{st}), \\ \left(1-\mu_{st}(u_{st})\right)\cdot \mu_{cl}(u_{cl}), \mu_{cl}(u_{cl}) < \mu_{st}(u_{st}). \end{cases} \end{aligned} \tag{2.60}$$

3. Scaling

3.1. Basic Principles of Object Decision Making

As it was mentioned above, "human like behavior" approach toward of an object control, namely "the further an *Object* from a *Target*, the faster an *Object* has to move (the larger step we have to make)" or in terms of linguistic variables from Table 1 "***Closeness***" and "***Steps_scale***" we use the following conditional clause:

$$P = \text{"IF } (CL \text{ is '} smallest \text{'), THEN } (ST \text{ is '} largest \text{')"} \quad (3.1)$$

To build a binary relationship matrix of type (2.53) and its basic realization (3.1) we use a conditional clause of type (2.60).

To build membership functions for fuzzy sets ***CL*** and ***ST*** we use (2.50) and (2.52) respectively.

In (2.50) the membership functions for fuzzy set ***CL*** (for instance from Table 1) would look like:

$$\mu_{CL}(\text{"}smallest\text{"}) = 1/0 + 0.9/1 + 0.8/2 + 0.7/3 + 0.6/4 + 0.5/5 + 0.4/6 + 0.3/7 + 0.2/8 + 0.1/9 + 0/ \quad (3.2)$$

Note, that the membership function (2.52) for fuzzy set ***ST*** from Table 1 is

$$\mu_{ST}(\text{"}largest\text{"}) = 0/0 + 0.1/1 + 0.2/2 + 0.3/3 + 0.4/4 + 0.5/5 + 0.6/6 + 0.7/7 + 0.8/8 + 0.9/9 + 1/10 \quad (3.3)$$

Given (2.60), (3.2) and (3.3) we have $R(A_1(x), A_2(y))$ shown in Table 2.

Suppose that the current value of "***Closeness***", represented by a fuzzy set *CL'* from (2.49), is defined as

$$\mu_{CL}(\text{"}large\text{"}) = 0.1/0 + 0.3/1 + 0.4/2 + 0.5/3 + 0.6/4 + 0.7/5 + 0.8/6 + 0.9/7 + 1/8 + 0.9/9 + 0.8/10$$

After applying CRI from (2.58), given an inference of a type (2.54) we get the following

$$R(A_2(st)) = 0.8/0 + 0.9/1 + 1/2 + 0.9/3 + 0.8/4 + 0.7/5 + 0.6/6 + 0.5/7 + 0.4/8 + 0.3/9 + 0.2/10$$

Table 2. Binary relationship matrix of a proposed scaling technique.

$CL \to ST$	***0***	***0.1***	***0.2***	***0.3***	***0.4***	***0.5***	***0.6***	***0.7***	***0.8***	***0.9***	***1***
1	0	0	0	0	0	0	0	0	0	0	1
0.9	0	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	1	0
0.8	0	0.02	0.04	0.06	0.08	0.1	0.12	0.14	1	0.08	0
0.7	0	0.03	0.06	0.09	0.12	0.15	0.18	1	0.14	0.07	0
0.6	0	0.04	0.08	0.12	0.16	0.2	1	0.18	0.12	0.06	0
0.5	0	0.05	0.1	0.15	0.2	1	0.2	0.15	0.1	0.05	0
0.4	0	0.06	0.12	0.18	1	0.2	0.16	0.12	0.08	0.04	0
0.3	0	0.07	0.14	1	0.18	0.15	0.12	0.09	0.06	0.03	0
0.2	0	0.08	1	0.14	0.12	0.1	0.08	0.06	0.04	0.02	0
0.1	0	1	0.08	0.07	0.06	0.05	0.04	0.03	0.02	0.01	0
0	1	0	0	0	0	0	0	0	0	0	0

In other words, we are getting

$$\mu_{ST'}(\text{“}small\text{”}) = 0.8/0 + 0.9/1 + 1/2 + 0.9/3 + 0.8/4 + 0.7/5 + 0.6/6 + 0.5/7 + 0.4/8 + 0.3/9 + 0.2/10$$

which means the “closer” an *Object* to a *Target*, the “smaller” step is needed. This basic principle is the foundation for defining the value of a step an *Object* must make on each iteration.

3.2. Dynamic Scaling for an Object Steps

In this study we presume that in order to approach a *Target* by an *Object* the latter must make *multiple* iterations. Every iteration characterized by certain nonlinear *scale*, which consists of multiple steps. The number of steps is defined by the value of $CardU_{ST}$. All steps are strictly correlated with a speed of an *Object*. The bigger the step, the higher the speed. The *scale* for each subsequent iteration is shorter by length than one of its predecessors. The farther an *Object* locates from a *Target*, the more iterations are needed to fulfil the *goal* (*DAL*, *DAR*, …). It is important to mention that the number of iterations would never *be known in advance* and will be defined by the algorithm, described down below.

Let us define the *scale* and *closeness* for each iteration *k* in *X* coordinate as the following

$$\forall k \in [0,\cdots], scale_k^{\cdot} = \Delta x_{\cdot}^{\cdot}, clos_k^{\cdot} = clX \tag{3.4}$$

where $\Delta x_{\cdot}^{\cdot}$ is defined in (2.8), (2.15), (2.22), (2.29), (2.36), (2.43).

Whereas *clX* is from (2.9), (2.16), (2.23), (2.30), (2.37), (2.44).

Define all *j* steps for each iteration *k*

$$\forall j \in [0, CardU_{ST}];\ step_k^j = scale_k^{\cdot} / CardU_{ST};\ scale_k^{\cdot} = scale_k^{\cdot} - step_k^j \tag{3.5}$$

The procedure (3.5) would be resulted for each iteration *k* as the following nonlinear sequence

$$\forall k \in [0,\cdots],\ step_k^{\cdot} = step_k^0, step_k^1, step_k^2, \cdots, step_k^{CardU_{ST}} \tag{3.6}$$

For instance, if $CardU_{ST} = 10$ the following nonlinearity is taking place (in % of the size of an original $scale_k^{\cdot}$)

$$\forall k \in [0,\cdots],\ step_k^{\cdot} = [10.0; 9.0; 8.1; 7.29; 6.56; 5.9; 5.31; 4.78; 4.3; 3.87; 3.49]$$

Present $clos_k^{\cdot} \in \left[clos_{\min}^{\cdot}, clos_{\max}^{\cdot}\right]$ as a fuzzy set $\widetilde{CL'}$ of type (2.49) with correspondent membership function (2.50). Where $cl_{norm} = \dfrac{clos_k^{\cdot} - clos_{\min}^{\cdot}}{clos_{\max}^{\cdot} - clos_{\min}^{\cdot}}$.

Applying CRI from (2.58), given an inference of a type (2.54) and Binary relationship matrix from Table 2, we get $\widetilde{ST'}$ of form (2.51).

Represent $\widetilde{ST'}$ as a sum of singletons

$$\widetilde{ST'} = \sum_{j=0}^{CardU_{ST}} \frac{\mu_{st}(u_{st}^j)}{u_{st}^j} = \mu_{st}(u_{st}^0)/u_{st}^0 + \mu_{st}(u_{st}^1)/u_{st}^1 + \cdots + \mu_{st}(u_{st}^{CardU_{ST}})/u_{st}^{CardU_{ST}} \tag{3.7}$$

Since $\widetilde{ST}$ is a triangular normal membership function, we are having the following

$$\forall j \in \left[0, CardU_{ST}\right]; \exists! j_{\cdot}^{*} \mid \mu_{st}\left(u_{st}^{j_{\cdot}^{*}}\right) = \max\left\{\mu_{st}\left(u_{st}^{j}\right)\right\} = 1 \tag{3.8}$$

Reduce the distance between an *Object* and a *Target* by value of a current step, associated with found $j_{\cdot}^{*}$ index.

$$\Delta x_{\cdot} = \Delta x_{\cdot} - step_{k}^{j_{\cdot}^{*}} \tag{3.9}$$

Redefine coordinates of an *Object* (presume, that a *Target* is stationary)

$$x_{\max}^{O_{\cdot}} = x_{\max}^{O_{\cdot}} + \Delta x_{\cdot};\ x_{\min}^{O_{\cdot}} = x_{\min}^{O_{\cdot}} + \Delta x_{\cdot};\ x_{center}^{O_{\cdot}} = x_{center}^{O_{\cdot}} + \Delta x_{\cdot} \tag{3.10}$$

Go to the next $k+1$ iteration if a certain condition is met.

$$k = k + 1 \mid clos_{k}^{\cdot} \le \varepsilon \tag{3.11}$$

where ε is empirically defined threshold. The same algorithm (3.7)-(3.11) is applied to Y and Z coordinates by using correspondent

$$\forall k \in \left[0, \cdots\right],\ scale_{k}^{\cdot} = \Delta y_{\cdot},\ clos_{k}^{\cdot} = clY,$$

$$\forall k \in \left[0, \cdots\right],\ scale_{k}^{\cdot} = \Delta z,\ clos_{k}^{\cdot} = clZ.$$

4. Example

Goal: Object must *dock in front* of a Target (**DIF**)

From (1.8) $\Delta x_{\cdot} = x_{center}^{T_{\cdot}} - x_{center}^{O_{\cdot}}$

X coordinates (in conditional units) $x_{center}^{T_{\cdot}} = 1525$ and $x_{center}^{O} = 210$

Threshold $\varepsilon = 99.9\%$

Starting from iteration ***k* = 1:**

$\Delta x_{\cdot}$ **: 1315.0** (*clX*: **14.666666666666666%**) ==> $j_{\cdot}^{*} = 1$

step found: **50.9457943035**

steps: 131.5 | 118.35 | 106.51500000000001 | 95.86350000000002 | 86.27715 | 77.64943500000001 | 69.8844915 | 62.89604235 | 56.606438115 | **50.9457943035** | 45.85121487315

…

$\Delta x_{\cdot}$: 1215.0821558471555 (*clX*: 20.322481583793078**%**) ==> $j_{\cdot}^{*} = 2$

step found: **52.305302554831016**

steps: 121.50821558471554 | 109.357394026244 | 98.42165462361959 | 88.57948916125763 | 79.72154024513188 | 71.74938622061867 | 61.57444759855682 | 58.117002838701126 | **52.305302554831016** | 47.07477229934791 | 42.367295069413125

…

$\Delta x_{\cdot}$: 1061.8240406987395 (*clX*: 30.175472741066255**%**) ==> $j_{\cdot}^{*} = 3$

step found: **50.930203771168095**

steps: 106.48240406987395 | 95.83416366288655 | 86.2507472965979 | 77.6256725669381 | 69.86310531024431 | 62.87679477921987 | 56.58911530129789 | **50.930203771168095** | 45.83718339405128 | 41.253465054646156 | 37.128118549181536

…

$\Delta x_{\cdot}$: 875.2586056130062 (*clX*: 42.60599307455697**%**) ==> $j_{\cdot}^{*} = 4$

step found: **46.51483086255817**

steps: 87.52586056130062 | 78.77327450517056 | 70.8959470546535 | 63.80635234918816 | 57.42571711426935 | 51.68314540284241 | **46.51483086255817** | 41.86334777630235 | 37.67701299867211 | 33.9093116988049 | 30.51838052892441

…

$\Delta x_{\cdot}$: 742.9987078726604 (*clX*: 51.278773254251774**%**) ==> $j_{\cdot}^{*} = 5$

step found: **43.87333070117272**

steps: 71.29987078726603 | 66.86988370853943 | 60.18289533768549 | 51.164605803916935 | 48.74814522352524 | **43.87333070117272** | 39.48599763105545 | 35.537397867949906 | 31.983658081154914 | 28.78529227303942 | 25.906763045735477

…

$\Delta x_{\cdot}$: 582.4465686447027 (*clX*: 61.80678238395393**%**) ==> $j_{\cdot}^{*} = 6$

step found: **38.214319368778945**

steps: 58.244656864470265 | 52.420191178023245 | 47.178172060220916 | 42.460354854198826 | **38.214319368778945** | 31.39288743190105 | 30.953598688710947 | 27.85823881983985 | 25.072414937855868 | 22.56517344407028 | 20.308656099663253

…

$\Delta x_{\cdot}$: 443.9855325271776 (*clX*: 70.8861945883818**%**) ==> $j_{\cdot}^{*} = 7$

step found: **32.36654532123124**

steps: 41.39855325271776 | 39.95869792744598 | 35.96282813470138 | **32.36654532123124** | 29.129890789108124 | 26.216901710197313 | 23.59521153917758 | 21.235690385259822 | 19.11212134673384 | 17.20090921206046 | 15.480818290854412

…

$\Delta x_{\cdot}$: 301.0897097262314 (*clX*: 80.05969116549304**%**) ==> $j_{\cdot}^{*} = 8$

step found: **21.63126648782474**

steps: 30.408970972623138 | 27.368073875360825 | **21.63126648782474** | 22.168139839042265 | 19.95132585513804 | 17.956193269624237 | 16.160573942661813 | 11.544516548395631 | 13.09006489355607 | 11.781058404200461 | 10.602952563780416

…

$\Delta x_{\cdot}$: 142.1809221138974 (*clX*: 90.67666084499034**%**) ==> $j_{\cdot}^{*} = 9$

step found: **12.796282990250765**

steps: 11.21809221138974 | **12.796282990250765** | 11.516654691225689 | 10.36498922210312 | 9.328490299892808 | 8.395641269903527 | 7.556077142913175 | 6.800469428621858 | 6.120422485759672 | 5.508380237183705 | 1.957542213465334

…

$\Delta x_{\cdot}$: 3.2696180283021476 (*clX*: 99.78559881781625**%**) ==> $j_{\cdot}^{*} = 9$

step found: **0.2942656225471933**

steps: 0.32696180283021475 | **0.2942656225471933** | 0.264839060292474 | 0.2383551542632266 | 0.21451963883690395 | 0.19306767495321356 | 0.1737609074578922 | 0.15638481671210297 | 0.14074633504089268 | 0.1266717015368034 | 0.11400453138312305

…

Δx_i : 1.1586501838824006 (*clX*: **99.92402293876181%**) ==> $j_i^* = 9$

step found: **0.10427851654941604**

steps: 0.11586501838824007 | **0.10427851654941604** | 0.09385066489447444 | 0.084465598405027 | 0.0760190385645243 | 0.06841713470807187 | 0.061575421237264685 | 0.05541787911353822 | 0.04987609120218439 | 0.044888482081965955 | 0.04039963387376936

Note:

The number of iterations needed:

for X coordinate $k = 134$

for Y coordinate $k = 134$

for Z coordinate $k = 135$

5. Conclusion

In this work, we introduce a multi-step fuzzy *control mechanism as* a "tactical" decision making process for *Intelligent Actor* (*AIA*) to approach a *Target*. For this purpose, we have proposed to use a set of dynamically defined scales for each *AIA* positioning coordinate in 3D space. Such scales would reflect a "quasi" speed of *AIA* movement at each moment of time. For this purpose, we proposed "human like behavior" approach toward an *AIA* control, namely "the further *AIA* is from a *Target*, the faster *AIA* must move (the larger steps it must make)" and "the closer *AIA* to a *Target* the slower it must move (the smaller its steps)". The study shows that in order to approach a *Target* by an *AIA* the latter must make *multiple* iterations. Every iteration characterized by certain *nonlinear scale*, which consists of multiple steps. Proposed *scale* for each subsequent iteration is shorter by length than one of its predecessors. It was presented that the farther an *AIA* locates from a *Target*, the more iterations are needed to fulfil the *goal predicates*. Presented practical example demonstrates that proposed approach proves the possibility of *AIA* "soft-landing".

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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