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Machine Intelligence Quotient as a Complex Fuzzy Numeral

V. C. I. Ulinwa

Abstract

Abstract. An ongoing research shows that machine intelligence quotient (MIQ) is an integrated complex numeral from three standard measures and transformable within the plane and other coordinates. With distinctive scales, technical, personal, and legislative, the multiple perspectives inquiring system (TOP) is used in calibrating, measuring, and interpreting the quotient. Given the homogeny of the linguistic Choquet fuzzy integral and linguistic complex fuzzy set theorems, on which the considered machine intelligence measurement is based, a new MIQ calculus is presented for consideration. The tenets are expected to withstand technological advancement and human interpretation.

Keywords. Machine Intelligence Measurement, MIQ, Machine Intelligence Quotient, Multiple Perspective Inquiring Analysis, TOP

1 Introduction

The investigated phenomenon, machine intelligence quotient, is controversial and important for electromechanical advancement [29]. One of the controversies is how to determine machines that think [28]. The other is how to figure their level of intelligence and representation [7] [13] [24] [30]. According to [12], machine intelligence is a result of some type of rules that are algorithmically coded on software or hardwired.

Although Zadeh [32] envisaged the concept of machine intelligence quotient (MIQ), Turing [28] testing primer and Searle [24] argument advanced the necessity as much as Descente's work laid the fundamental need [29] [31]. Ironically, little is still known about MIQ [3]. For these reasons, this study used the multiple perspective inquiring method (TOP) to elucidate a new measurement method. The invocation of ambiguous quantified tenets similar to human intelligence measurement is avoided. Rather MIQ is factually an aggregation of disjointed complex fuzzy sets, a nonunitary definition. It is unwise to use a single and the same indicator to qualitatively or quantitatively represent the intelligence or to use the indices of quality to presume quantity and visa-vis. This investigation also takes exception in equating performance as if it is the intelligence. Such a supposition is far fetched; performance measure is a sub measure of productivity. Rather, machine intelligence is relative to productivity because machine intelligence without a productive work is a waste. Also, human preference for quality than quantity and quantitative desire for more of quality things, with respect to machine intelligence, is reconciled. The quality is not about the outward appearance of a machine but about the implicit tangible. As such, this study uses a Cartesian fuzzy set to represent the intelligence.

2 Multiple Perspective Inquiring Method

To provide a valid and reliable measurement instrument that captures features in diverse but correlated machine intelligence domains, TOP scales are used. TOP minimizes statistical biases that are common in the quantitative science and practice; secondly, it discovers the underlying perspective meanings that affect the science of machine intelligence; three, it ratifies theory and data anchors of the intelligence that ground on more than one perspective; and four, it insures that the bases of any solution and thesis are within the domain peer experts and consumers recognize.

The presupposed calibration approach is grounded on the derivatives set forth by [16], [17], [22], [26], and [33] because it is imperative to lay down a comprehensive and standard method for measuring the intelligence. Moreover, TOP brings to bear, in any given machine intelligence measurement the factors [16].

2.1 Technical Perspective (T)

The quantitative science of machine intelligence measurement requires T perspective, a tenet that numerically justifies every means and results. It uses the science to isolate, abstract, idealize, and simplify problems into solutions [22]. For the measurement to be a major scientific function, results must be quantitatively analyzed, interpreted, and reported.

A five-theoretic topology [6], with a distinct name of a philosopher: Leibniz, Locke, Kant, Hegel, and Singer, is crucially used to explain this perspective [8], [16]. For the Leibnizian, truth is analytical and can be mathematically reduced into a solution space. To the Lockean, truth is experimental and in any given problem peer experts' scientific opinion determines if a solution is acceptable or not. The Kantian inquiring analysis rests on the assumption that truth is synthetic and only through two complementary solution models. Null and alternative hypotheses are developed for accepting or rejecting any practice that is hard to be studied with the Lockean or the Leibnzian method. To the Hegelian, analysis is grounded on the premise that truth conflicts and only through formulation of antithetical representation. The Singerian inquiring analysis emphasizes on pragmatic methods relative to the general purpose and objective of an inquiry [6],[16].

2.2 Organizational Perspective (O)

Organizational filter, legislative filter as it is in this case, is for observing and analyzing an organization's tenets of machine intelligence. The O perspective relies on policies and ethics. For example, it insures that the intelligence is within the acceptable scientific practices. It determines the standard and conditions for rigorous issues. Generally, the O perspective does not seek optimal solutions but emphasizes on compromise and routine.

2.3 Personal Perspective (P)

The personal perspective is very subtle compared to the others. It brings to bear the psychology, ethics, and sociology of those whose decisions affect machine intelligence, and these factors are inseparable from any model [8], [16]. It brings human persona or the eye of an individual into measurement science and practice. It is the unique insight and intuition for analysis [16].

3 Machine Intelligence Measurement

When one observes certain machinery systems, there abound manifests that appeal and in some cases are the cursors of the intelligence. As such, a scientific approach is needed to determine and measure the intelligence in controllable scientific contexts.

3.1 Contexts

The first thing is to define the appropriate contexts. The contexts are the informational descriptions and explanations about the system, its domain, resources available to it, and contribution to humanity. They characterize the situations. Events are just the sub-summaries of the contexts.

But in what contexts should the intelligence be tested? One should avoid testing only in contexts in which the purpose of the intelligence is predictable or obvious. This approach is not promising for the system behavior is known. The test, instead, should be conducted in controlled contexts such as normal, sudden, rare, and where or when the purpose is barely present.

Events in a normal context are the types system designers generally model for. They are well defined and predictable and usually unwanted events are generally minimized or eliminated; sudden events occur unexpectedly; rare events are those the designers consider to be possible but least probable and they are sometimes quite catastrophic or beneficial and very difficult to detect; and less purposeful event is one in which the purpose of the system is barely present in the environment.

Given the contextual event, the focus should be on what Ji and Chen [14] characterized as knowledge incompleteness, motivation correlativeness, and initiative openness. Knowledge incompleteness occurs when events are so-new to a system and it is unable to deduce knowledge from its base. On the other hand, motivation correlativeness is due to events that positively or negatively impact the achievement of goals. Finally, initiative openness helps explain opportunities that partially open to a system control for promoting benefits or reducing and avoiding cost relative to measurable. Numbered equations must be managed manually.

3.2 Measurable

Although there is no general list of acceptable factors of machine intelligence, the identified relevant qualitative and quantitative measurable or factors, used in this study, are impedance, machine (process) capability, productivity, versatility, and agility, to list a few. Figure 1 shows how conventional measures, with respect to the measurable, are sorted as T, O, or P.

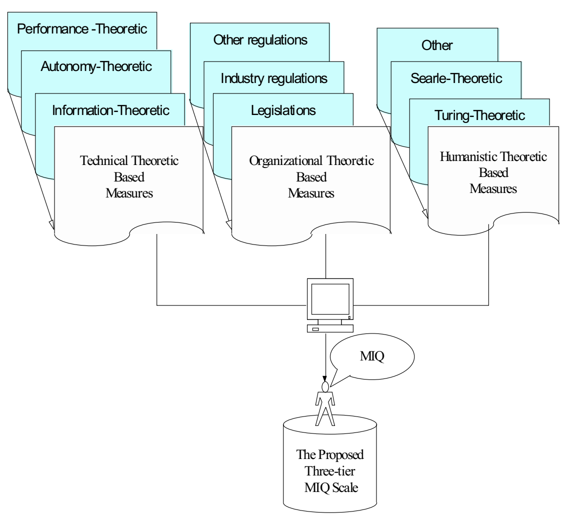

Figure 1. TOP Classified Measurable

From Figure 1 it is evident that Turing test and the Searle's argument are within the humanistic category and the information-theoretic or autonomous theoretic measures are in the technical kind. To the technical school, machine intelligence is all but qualitative manifest. This induces the search for a universal numerical meaning such that any qualitative feature is unscientific. The purpose is to operationalize properties of the intelligence in terms of behavioral actions that can be mathematically measured and manipulated.

Measuring machine intelligence is elusive and subtle with the personal perspective than the T or O. The qualitative measure is usually from an individual's eyes and mental representation; and it is grounded on human charisma and interest. From this point of view, it is the persona of human intelligence and it filters in qualities parallel to the manifests of human neural and social implications. In other words, it is a general logic that contains no precepts but a rule-governed manifestation [15]. It is therefore evident from Figure 1 that measurable for T oriented measures such as information or performance measures are different from those for O and P. The standardization consists of using T to quantify factors such as productivity, O to assess compliance of the intelligence to the relevant regulations, and P to assess the socio-psychological aspects. The latter should include the concerns of Turing [28] and Searle [23]; and it is like tasting wine or rating movies or music.

To start with, let O be a set of observations such that $o_i \in O$ and $b_i \in B$ represent a time series observable machine behaviors during an event type e_i. If $e_i \in E$, $b_i \in B$, and $o_i \in O$ then the following are:

1. Determining relevant measurable relative to machine intelligence;
2. Determining machine productivity during each event type;
3. Deriving a technical measure of machine intelligence;
4. Deriving a legislative measure of machine intelligence;
5. Deriving a humanistic measure of machine intelligence; and

6. Determining MIQ from 3, 4, and 5 relative to the effects of 1 and 2

Given these conditions, the first thing is to convert T, O, P measures to complex fuzzy sets. The procedural method starts with fuzzy linguistic variables [18] [19]. A linguistic variable is a quintuple $(x, T(x) U, G, M)$, where x is a variable, *T(x)* is a set of the variables in a universe U and G is a syntactic rule that generates the linguistic values. M is a rule relating meanings of the linguistic values such that fuzzy relations, the interaction between the components of complex fuzzy numbers, are meaningful [20] [21].

Thus T, O, and P as linguistic variables consist of laced labels; each label specifies a focal point of the measurement. The most common methods are a fuzzy triangular, a trapezoidal, and an exponential functions as shown in Equations (1), (2), and (3) where LS means linguistic set [25]; and resemble the ones shown in Figure 3:

$$L_s = \int_{-2}^{0} \left(\tfrac{2+x}{2}\right) \Big/ x + \int_{0}^{2} \left(\tfrac{2-x}{2}\right) \Big/ x \tag{1}$$

$$L_s = \int_{-4}^{2} \left(\tfrac{4+x}{2}\right) \Big/ x + \int_{2}^{2} 1/x + \int_{2}^{4} \left(\tfrac{4-x}{2}\right) \Big/ x \tag{2}$$

$$L_s = \int_{x} e^{-5(x-5)^2}/x \tag{3}$$

In Figure 2, (a) is a triangular set, (b) is a trapezoidal set, and (c) is a Gaussian set. Notice that the sets are the result of a membership function that $f(A) \longrightarrow [0,1]$ assigns numbers in $[0,1]$ interval to subsets of a universe of discourse μ [9] [10] [18]. Using scale 5.45c, number 3, from [4] each of the labels of T, O, and P measures is characterized as 'very unsatisfactory', 'unsatisfactory', 'partially satisfactory', 'satisfactory', or 'very satisfactory' with unique fuzzy numbers [4] [5]. With Equations (4) and (5), fuzzy projection, each of the linguistic variables is transformed to a linguistic complex fuzzy set such that [19]:

$$proj[R;X] = \int_{x} \left(\max_{y} \mu_R(x,y) \right) /x \tag{4}$$

$$proj[R;Y] = \int_{x} \left(\max_{x} \mu_R(x,y) \right) /y \tag{5}$$

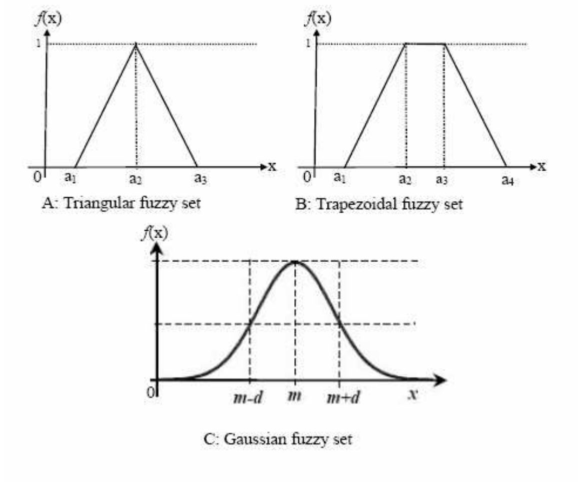

Figure 2. Common Membership Types

Although [10] suggested $\overline{X} = \int_{Ux} [\subset U_y \wedge \mu_R(x,y)]/x$ and $\overline{Y} = \int_{Uy} [\subset U_x \wedge \mu_R(x,y)]/y$ for completing the transformation, linguistic Choquet fuzzy integral [1] [2] [10] is recommended instead. The resulting set is the linguistic complex fuzzy set [2].

4 Complex Fuzzy Set

4.1 Background

A linguistic complex fuzzy set $z = x + jy$, in a Cartesian coordinate, is composed of two linguistic fuzzy sets [19]. One for a real number Re(z) and the other for the imaginary part Im(z). Each relates to a specific dimension such that $z = x + jy$ is information on the X-axis and the Y-axis of the set. Intuitively, arithmetic operations can be performed on such sets [9] [19] [20] [21]. Given two such sets $Z_1 = (x_1 + jy_1)$ and $Z_2 = (x_2 + jy_2)$ then $Z = Z_1 + Z_2 = (x_1 + x_2) + (jy_1 + jy_2)$. Because [9] noted that it is easy to perform division operation in polar plane,

Z is transformed to a polar plane such that $p^{\theta} = Z = (x + jy)$ where $\mu_1 (x + jy) = \theta$ and $\theta = p = \sqrt{x^2 + y^2}$. Notice that $\theta = \arctan\left(\frac{y}{x}\right)$. If $Z_1 Z_2$ or $\frac{Z_1}{Z_2}$ is in a polar plane then Z_1 and $Z_2$are also polar coordinated [19]. These operations are applicable to machine intelligence measurement.

4.2 Application to Machine Intelligence Measurement

Like any other implicit tangible goods, machine intelligence is a purposeful creation. Setting it relative to economic values is intuitive and meaningful for productive endeavors. Therefore, the first step is to set machine intelligence relative to O or a compliance measure. Figure 3 is an example. This is done by fixing compliance along the X axis as x for T or P along the Y axis. The fixation, an aggregated value, is determined with linguistic Choquet fuzzy integral [1] [2].

With $(C) \int f d\mu = \sum_{i=1}^{n} (h_i - r_{i-1}) \mu(A_i)$, a standard Choquet fuzzy integral defined over nonadditive measures [10],

$$\int_c h \circ g = \sum_{i=1}^{n} h(x_i) \left[g(X_i) - g(x_{i-1}) \right] \tag{6a}$$

or

$$\int_c h \circ g = \sum_{i=1}^{n} g(x_i) \left[h(X_i) - h(x_{i-1}) \right] \tag{6b}$$

defines the lower and upper bounds of the linguistic fuzzy sets intervals such that

$$\int_c h \circ g = \bigcup_{\alpha \in [0,1]} \left[\int_c h \circ g \right]. \tag{6c}$$

It is evident from [1] [2] that such

$$\left[\int_c h \circ g \right] = \left[\int_c \underline{[h]_\alpha} \circ g, \overline{[h]}_\alpha \circ g \right] \tag{6d}$$

is a linguistic Choquet fuzzy integral where

$\underline{[h]_\alpha = [h]_\alpha}$, $\overline{[h]}_\alpha$, $\left\{ h \in R | \underline{[h]_\alpha} \leq \overline{[h]}_\alpha \right\}$, and $0 \leq \alpha \leq 1$.

Given the integration, it is clear that subsethood of T and P quantifies MIQ after conditioning T and P to the compliance measure O; meaning that

$$MIQ = S(T,P) = \left(\frac{|T \cap P|}{|T|}\right)\left(\frac{|T \cap P|}{|P|}\right) \quad (7)$$

with $\cap$ as a standard fuzzy interception operator.

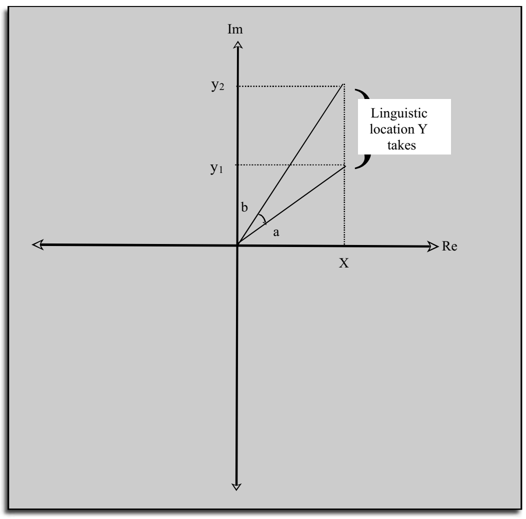

Figure 3. Common Membership Types

To profile the machine given a contextual event and taking linguistic variables or fuzzy numbers as inputs, m^T observations are taken on n measurable. If $t_{ij} \subset T$, $l_{ij} \subset O$, and $p_{ij} \subset O$ measure the system behavior such that $f(x_{ij}) = [t_{ij}, l_{ij}, p_{ij}]$ then

$$T_{ij} = \frac{t_{ij}}{\sum\limits_{i,j=1} t_{ij}},\ L_{ij} = \frac{l_{ij}}{\sum\limits_{i,j=1} l_{ij}},\ \text{and } P_{ij} = \frac{p_{ij}}{\sum\limits_{i,j=1} p_{ij}}. \quad (8)$$

Each is further normalized with its direct variance with golden ratio such that $y = kw$, where k is the constant of proportionality of the greatest j^{th} column value and golden ratio: 1.618. Notice that y varies as x; and k is used to obtain new normalized T_{ij}, L_{ij}, P_{ij} values.

Next, a composition of fuzzy relation on each event E_i and its transpose E^{-1} is taken such that

$$E \circ E^{-1} = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ : & : & : \\ r_{n1} & \cdots & r_{mn} \end{bmatrix} \circ \begin{bmatrix} r_{11} & \cdots & r_{n1} \\ : & : & : \\ r_{1m} & \cdots & r_{mn} \end{bmatrix} \quad (9)$$

where $E \circ E^{-1} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \circ \begin{bmatrix} a & c \\ b & d \end{bmatrix} =$

$$= \begin{bmatrix} a \cap a \;\cup\; b \cap b & a \cap c \;\cup\; b \cap d \\ c \cap a \;\cup\; d \cap b & c \cap c \;\cup\; d \cap d \end{bmatrix}.$$

It involves taking the maximum of the minimums per row of a fuzzy projection. Finally, from [5] a matched ratio (MR) of the projected fuzzy set and each of the reference set is calculated using

$$MR = \frac{1}{2} \frac{\int_{s_y} \mu_{\overline{y}}(y)dy + \int_{s_y} \mu_{\tilde{\overline{y}}}(y)dy - D}{\int_{s_y} \mu_{\overline{y}}(y)dy}, \quad (10)$$

where $D = \int s_{\overline{y}} \cup s_{\tilde{\overline{y}}} |\mu_{\overline{y}}(y) - \mu_{\tilde{\overline{y}}}| dy$.

Given a highest matched ratio, the idea is to select the reference set corresponding with the projected set. The selected set then becomes the linguistic variable representing the profile. Alternatively, the crispy numbers that represent the reference sets could be used directly for the measurement. Letting $\widetilde{L}_{ij}$ be the linguistic variables, $N = \left\{ \widetilde{L}_{11}, \widetilde{L}_{12} ... \widetilde{L}_{1m} \right\}$, and knowing that $\widetilde{L}_i = [a_i, b_i, c_i, d_i]$ and $i \in 1, 2, ..., n$, trapezoid with parameters defined by

$$\overline{\widetilde{L}}_i = \tfrac{1}{n} \bigoplus_{j=1}^{m} \widetilde{L}_{ij}, \quad (11)$$

then Equation (11) is the extension principle of addition of fuzzy means [4]. The steps are repeated for all the measurement contexts. Thus with a given n number of measurable there are associable n rated machine behavior and n productivity to explain the system's profile from a linguistic variable.

5 Conclusion

When one observes a machinery system there abound manifests that appeal and in some cases act as cursors for attributing intelligence to it. What is arguable is how to measure the intelligence ordained on them. Equally controversial is how to represent them. The postulation used in this paper consists of three perspectives: technical (T), organizational (O), and personal (P). Each calibrates the intelligence differently. The T is the most traditional, quantitative, method of measuring observation; the O measures compliance of a machine to certain legislated criteria; and the P takes humanities into the measurement and interpretation.

Because each gives a different definition and measure of the intelligence, it is only when T, O, and P are integrated that one derives a meaningful measure. This is important when a machinery system manufacturer, regulatory agency, or a user ascribes intelligence to the orderliness; or an observer tests if a machine is intelligent. The endeavor is that a machinery system is not intelligent until it is measured against the required purpose, compliance to a certain regulation, and what humans understand as showing intelligence.

For each defined measurement context, the T filter should be used to quantify the manifest using input and output relations. Focus should also be on machine productivity relative to each context. The O perspective should be used to measure compliance of the system to any regulation during each context. This requires using any standard compliance measure as assessment tool or a new one constructed. This measure is important because any intelligent system that is not incompliance, for instance, to a required act of congress or an executive order is stupid with respect to this perspective. In addition to the T and O calibrations per the contexts, P requires the use of socio-psychology scale.

Figure 4 shows the independent filters as used for defining and measuring the intelligence. The presupposed concern is the region of interception. The region is where all agree on what is intelligent. The sets can overlap more or be null depending on the system behavior. So far the indices are meaningless until cross-cued. The meaningfulness necessitates linguistic complex fuzzy set theory.

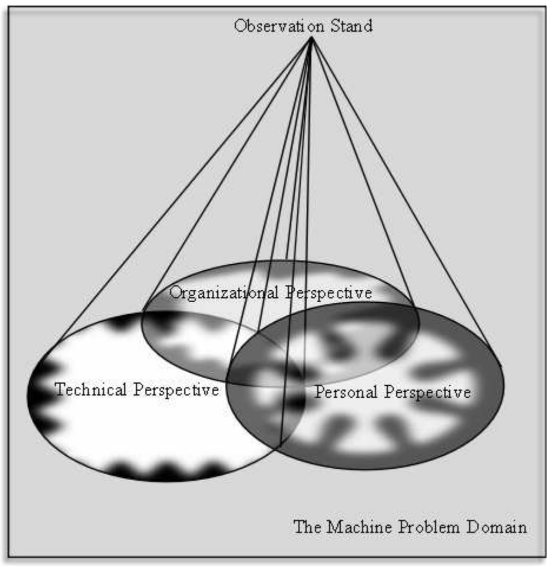

Figure 4. Common Membership Types

This grammatical sketch exposes new approach to define and articulate machine intelligence and the quotient. With this approach, one can fuse some variables and fix another for a controlled measurement. The linguistic method allows even a novice to understand what is measured. The tent is that unproductive intelligent machinery is a waste.

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V. C. I. Ulinwa,

Received March 26, 2007

Walden University School of Education, USA
E–mail: *iulinwa@waldenu.edu*