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Human-Machine Interaction: Causal Dynamical Networks

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Abstract. The objective of this paper is to introduce a modified version of the Causal Dynamical Networks (CDN) algorithm for application in the human-machine interaction. It is demonstrated that an individual does not interact with one robot, but with a multitude of personalities stored in the robot. These personalities are independent of each other. A robot thus does not have a unique personality. In order for a robot to become a unique individual a new algorithm is proposed. The new algorithm is called the Causal Form Fluctuation Network (CEFN). It is shown that such an algorithm can help machines develop similar to human general intelligence capabilities such as interpretation, wisdom (acquiring knowledge), and prediction (intuition). Also to be able to make decisions, have ideas, and imaginations.

Key words: Dynamical interactions; causal dynamical network; disordering locality; non-local links; complexity; entropy; disequilibrium.

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1 Introduction

Imagine that you buy a humanoid robot first hand. The robot is programmed by an engineer. Once you buy (him/her) you are in fact interacting with the engineer who designed the humanoid robot. The robot has the same characteristics as the engineer. When you buy the humanoid, you are interacting with one other person (the engineer), first hand. As time goes on, the engineer's personality and characteristics change, but not the traits he has programmed in the robot. The robot does not evolve in time, the artificial intelligent programming allows for accumulation of scenarios. The traits programmed by the engineer stay unchanged. This means that you evolve and change in time, but the robot stays the same, unless you add new modules to his original programming. In this case, you are dealing with two people, the original engineer and yourself as you are at the time of programming. Now, if you sell the robot, the buyer has to interact with the original engineer, and you. If the buyer adds a programming of his own, then in his interaction with the robot the buyer interacts with three people, the initial engineer, you and himself. If this process goes on, every successive person (i) has to interact with (i+1) people.

This situation can be modelled as a connected graph or a network. In this particular type of network space plays no role. It is the dynamical interaction that provides connections that is of major interest. In this context the fundamental element is not time but rather “causality". It is the causality the reason behind connections getting turned “on" and “off". The “on", “off" appearances of links create a dynamic network based on causality. Causality manifests itself in time. Thus connections are turned “on", “off”" in time. Causality can be divided into cause-n-effect. A cause is the motive that provokes an individual to interact with a humanoid robot. An effect is the consequence of a cause. Each cause-n- effect can be represented by a link with (2) nodes. The beginning node represents an individual, and the end node represents a humanoid robot. A causal dynamical network is a network created by cause-n-effect links. The network is dynamic because links can appear or disappear in time. An example of such a dynamical cause-n-effect network is given Figure 1.

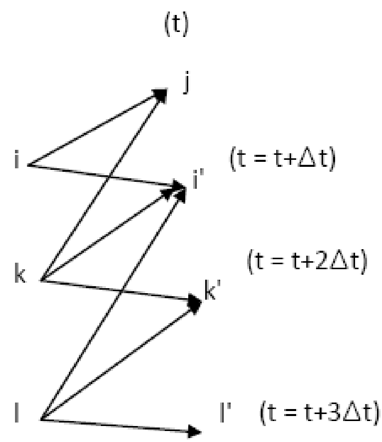


Figure 1. A dynamical cause - n- effect network

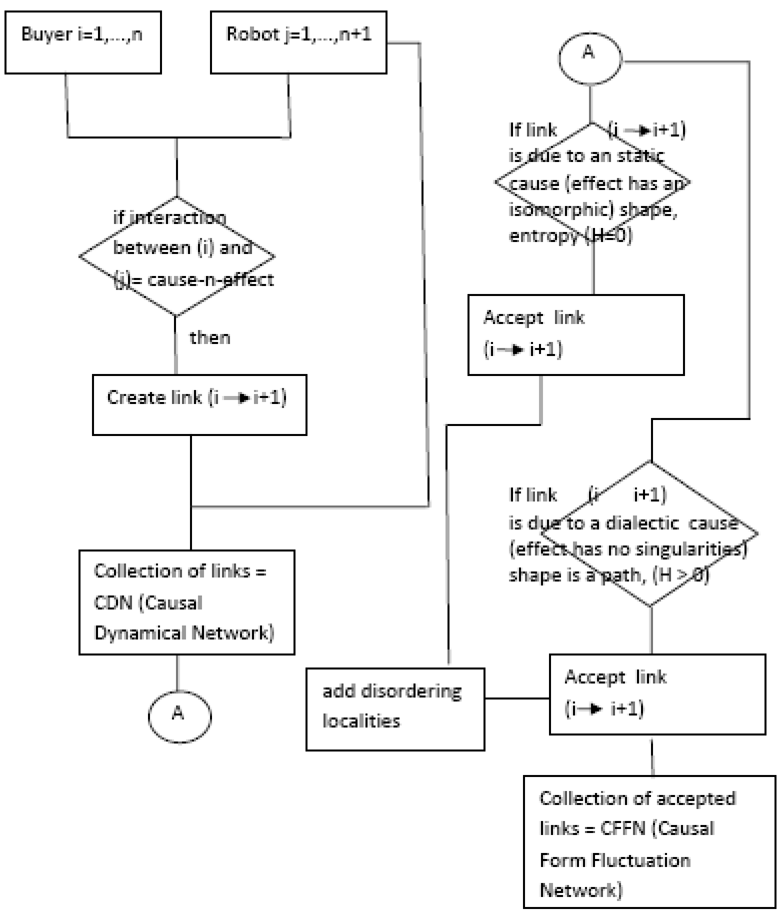
In Figure 1, buyer(i) purchases a humanoid robot at time (t). At this point buyer (i) interacts with the engineer programmer (j) through the robot. At this point there exists only one edge that represents the interaction between buyer (i) and engineer (j). At time ($t + \Delta t$) buyer (i) decides to add new programming modules to enhance the robot. At this point buyer (i) is interacting with (2) people, the initial engineer (j), and himself, noted as (i'). Therefore, there are two edges connecting buyer (i) to (j), and (i'). If at time ($t + \Delta t$), buyer (i) decides to sell the robot to buyer(k), then initially, buyer(k) interacts with (2) people, initial engineer (j), and the buyer (i) as he was at time ($t + \Delta t$), which is represented by (i'). Initially, for buyer (k), there exists (2) edges, that represent the interaction of buyer (k) with (j), and (i'). Let's assume that at time (t+2Δt), buyer (k) decides to enhance the robot by adding some programming modules. At this point buyer (k) is interacting with the initial engineer (j), buyer (i) as he was at time (t+ Δt), (i'), and himself as he is at time ($t + 2\Delta t$), denoted by (k'). Therefore, the network initially created through interaction between (i),(j), and (i') is expanded as connections between (k), (j), (i'), and (k') are created. So, each consecutive buyer (l) has to deal with (l+1) people. Selling the humanoid robot does not erase previous connections, since at any point in time a sell can occur backwards, meaning that the new buyer could technically sell the robot back to the old buyer with an added value being enhancement through new programming modules. This process can be repeated indefinitely. If the programming of human (i-1) is erased when human (i) programs the robot, this has no impact on the CFFN network. The links created through cause-n-effect are saved in the CFFN network. This is because the method introduced here is not equivalent to a set of if-input-then-output rules which is similar to an expert system, [1], [2], and which has been proven to be very impractical if used to describe the personality of an artificially-intelligent system. The CFFN is based on the analysis of cause-n-effect which is not equal to if-input-then-output approach. Each cause has many levels or degrees of importance with respect to effect, which means that each cause level produces different effect intensity. This is discussed later in the paper.

In order to construct this network, the approach developed by [3], [4], [5], [6], [7] is used. As can be seen from Figure 1, the geometry of space in this type of network is dynamical. Connections can appear or disappear given the causal background. What is interesting to note is that this type of network has no fixed boundaries. As it is possible to interact simultaneously with a version of a person through the robot, then it is possible for a widely separated nodes to interact or connect with each other. Therefore, there exists, using the terminology of [8], a disordering locality, with edges added called non-local links. As can be deducted from the nature of such a network, there is no space, just a network of interactions with every node having the potential of being connected to every other node. However, the existence of non-local links in the network implies also the existence of disequilibrium. The objective of this paper is to explain the CDN introduced earlier, and analyse it's characteristics. Is such a complex system an improbable configuration. Disordering locality and non-local links introduce complexity to the CDN, which results in disequilibrium. It is investigated whether a causal dynamical network ever reaches entropy. In general, does such a system reach a low entropy fluctuations in a static equilibrium environment. In a causal dynamical network, is entropy a necessary and sufficient condition. In a causal dynamical network, is entropy stable. Is it local or general. What are the consequences of a long term disequilibrium or entropy. Finally, what are the advantages, and disadvantages of such a complex system of interactions, and is such a system of interactions time asymmetric in such a way that complexity and structure evolve. In this paper some general arguments are given as answer to the above questions. The proofs are given in a sequel paper to the present one.

The advantage of (CDN) representation of man-machine interaction is that it provides a way for humans to have a better interaction with machines. In order to render machines human like intelligent, i.e. more independent and individual, an algorithm is proposed. This algorithm which is an extension of the (CDN) is called Causal Form Fluctuation Network (CFFN). Up to the present, the Artificial Intelligences' latest attempt to make machines intelligent are algorithms such as the "neural networks" algorithm,[9], [10], and the most recent and more promising "deep learning" algorithm. The aim of both of these algorithms, [11], [12], [13], [14], is to help machines teach themselves and eventually be able to make good decisions. In this case a good decision is an appropriate response to a particular situation or circumstance. Decision making is a complex process. A decision can be considered as an effect due to an spectrum of causes. In strategic games where no human trait other than reaction and experience is required machines do better than humans, since they can act faster, and own a stock pile of recorded strategies to compare and draw from. An example of such a case is the case of a "neural networks" algorithm versus an experienced game of "Go" player. Recently, in a match between the algorithm and a top-ranked player Lee Se-dol, it was the algorithm that won the match. Many factors could have contributed to the defeat of the human challenger such as his state of mind at the time, stress, fatigue, anxiety, anger, and memory problems. Also his physical state such as his reaction time, health problems, and other multitude of physical and mental causes could have played a role in his defeat. Algorithm has no such problems. As long as all the connections are functioning the algorithm is executed. But in more complicated situations where human trait is needed, this is where the machines fail almost all the time. They lack what humans may call a "soul", a combination of wisdom, intelligence, emotions, imagination, goals, and many other factors. Machines do not think for themselves. They exclusively react. The cause-n-effect on the side of the machines is to verify that a cause is matched with one of the modules installed, (machine cause), and execute the corresponding effect, (command), (machine effect). (CFFN) is one possible way to convert machines to unique individuals.

Humans make decisions and react because of the following causes: 1) needs, such as a need to eat or sleep, and in general satisfy physical needs. 2) Emotions: this is a trait that helps humans deal with tough and complex situations. 3) self-awareness: this is being aware of their existence, and mortality. 4) Ageing, meaning changing physical and mental characters. 5) Evolving: or as commonly known becoming wiser, and smarter at dealing with life's complicated situations. 6) Curiosity: this trait is encrypted in our genetic code as a survival device. 7) Instinct: somehow knowing how to interpret and react to a situation. 8) Sense of gain: this is the urge to enter a competition and try to win. and finally, 9) imagination is a human characteristic that serves as a survival tool, and finally 10) wisdom. Machine have no needs, no emotions and no Self-awareness since they can be turned off at any time. Machines do not age. Machines evolve in a different way, they accumulate scenarios and collect data. They react according to a set of codes triggered by comparing clusters of data (scenarios). It is difficult to code human quality into machines. The latest attempt is to imitate brain cells. In particular, brain cells called neurons. This is done by building virtual or substitute neurons. Just as brain neurons the virtual neurons transmit information to each other through signals called synaptic strength. By creating a network of neurons with transmitting signals, it is assumed that the pattern produced is capable of recognizing images or dialogues. In order to complement, the AI, a new method of machine learning is proposed. The idea is that machines learn by interacting with humans. This interaction is represented by links. A collection of these links is a network. An extension of this network by creating form fluctuating links is a network that turns the CDN into a unique network that represents a unique machine. The claim of this paper is that it is possible to part human qualities into machine. This can be achieved through a network of interactions between humans and machines. This network is the (CDN). Each time an interaction occurs, a link is created. This link represents a cause-n-effect transfer from human to machine. A machine can be programmed to recognize each cause and associate it with an effect. In a way it is similar to pattern or dialogue recognition, since the machine has to collect this data and store it. The question is how can the machine internalize these characteristics and make them unique to correspond to that individual machine? The answer is provided by extending the (CDN) to include form fluctuating links, and thus creating the (CFFN) .

It is emphasised that it is through interaction that humanoid robots can acquire human like traits. Some may consider that this is a limited view of the cognitive robotics in general. For example robots can have interpretation capabilities through semantic programming, and that research has shown how interpretation can be obtained and can even generate interpretation rules automatically from spectral data, [15], [16], [17], [18], [19], [20], [21]. Of course the counter analysis to this argument is that even humans have great difficulty when it comes to interpretation. Interpretation is a function of an individual's innate personality, upbringing, culture, environment, intellectual level, attention level, and many more factors. A humanoid robot lacks at least half of the above factors. Therefore, therefore a humanoid robot cannot be programmed to interpret. The only possible way for a humanoid robot to acquire this capability is to build a CFFN network through interaction with real humans. This way only those links that have a positive cause-n-effect with respect to interpretation are preserved. The same argument The same scepticism exists when it comes to knowledge-acquisition. Some researchers claim that there is a whole field of study known as knowledge-based AI, which deals with acquiring knowledge that are used in robot programming, [22], [23], [24], [25]. The counter argument is that it depends on how you define knowledge. Robots can accumulate data and form them into scenarios. Knowledge has a more spiritual tone to it. Based on the logic of CFFN, only those links in the network are preserved that have either static or dialectic causes that produce either isomorphic (similar shapes) with no edges, or shapes with no singularities, and paths. This is discussed in more details later. In brief, not every data is stored and used, but only those data are used that have positive effects. The humanoid robot can only achieve such a capability by interacting with humans in a cause-n-effect environment. Some argue that one of the main applications of machine learning is prediction based on observed data. For example, Kalman Filtering is used to carry out prediction as one of its fundamental steps, [26], [27], [28], [29]. The counter argument is that if prediction is a regression based on data, then yes robots can predict based on mathematical logic. Kalman filters allow for a very accurate prediction, but this is only true when all cause and effect variables are well defined and identified. In general, this is not true. The CFFN method allows for a more accurate identification of cause-n-effect. Again, only those cause-n-effect interactions are retained that have positive outcomes with respect to prediction capabilities. This allows for not only prediction but also human like intuition, and anticipation, that normally would drive humans to make more or less correct decisions. Flow chart 1, summarizes and outlines the general procedure for creating CDN, and consequently CFFN. Details are explained in later sections.



Flow chart 1. Procedure for creating CDn, and CFFN

2 Causal Dynamical Networks

Let $(\{i\}; i = 1, \ldots, n)$ be the number of vertices that represent persons. In the context of this paper it is those who are in contact with a humanoid-robot either as owners or are in contact due to chance. Let $(\{j\}; i = 1, \ldots, m)$ be the number of vertices that represent humanoid-robots. Some clarification is necessary. Initially, there is one humanoid-robot that represents the original engineer or programmer who installed initial modules. If the humanoid-robot is bought at time (t), then after some lapse of time ($t+\Delta t$), the owner may install new programs or modules into the humanoid robot. At this point, one can consider that the number of robots are (j + 1), where (j = 1). There are two robots, the original that is programmed by the engineer, and the one that is programmed by the owner. Therefore, the total number of robots (m) depends on the total number of owners and human contacts with consequence, meaning those who added new modules to the robot, $(m = i + 1)$ Here (1) represent the original engineer. A good example is a fully automated car. Let's assume that it is programmed to stop when encountering an obstacle by an engineer. A driver wants this car to stop because he feels dizzy and wants to rest at a road curbside for a few minutes. Driver commands the automated car to stop, but this is in conflict with the initial programming that says stop when obstacles. The automated car does not respond to the command unless it is added a new program that allows it to accept occasional stops. The same scenario applies to variations in speed and spacing and lane changing.

The occurrence of each node is due to what is called cause-n-effect. A node is either "on" or "off". Each node in the set $(\{i\})$ is a tensor that represents an effect. An effect is a transformation of causes. Each vertex (i) is a casual set. It's existence is due to a set of causes interacting in a tensor form. Each two vertices are connected by an edge $(E(G) = \{e_{ij}\}; e_{ij} = 1,\ \textbf{if}\ e_{ij} \in E(G); 0\ \textbf{if}\ e_{ij} \notin E(G))$, where $(E(G))$ is the set all edges (E), in graph (G). Each link (e_{ij}) connects two nodes $(\{i, j\}; i \neq j)$. Each link is either turned "on", or "off". A link is turned on when two vertices are interacting. A link is turned off when there is no interaction between two nodes. For a human vertex (i), the effect tensor is formulated as $(y^i_{r1}(k) = \Lambda^i_{r1}(k) \otimes x^i_{r1}(k); r1 = 1, ..., N; i = 1, ..., n)$. (r1) is the number of commands, with a finite limit equal to (N). (k) is the number of traits of individual (i). There exists a finite number of traits equal to (M). $(y^i_{r1}(k) \in R^k)$ is a tensor in (k) dimension. $(\Lambda^i_{r1}(k))$ is a transformation matrix of size $(k \times k)$. $(x^i_{r1}(k))$ is the vector of causality for individual (i) with (k) number of traits. Each trait(k), has a level of importance. Usually among $(k = 1, ..., M)$ traits, one is the strongest. It is assumed that the strongest trait is the reason for the existence of cause-n-effect. For example, in this paper (10) traits are identified. For each individual these traits have different levels of importance. It is the trait with the highest level of importance or the strongest trait that provokes an individual to react. A trait is considered to be a cause. A reaction is considered to be an effect. Just like a cause, an effect has different levels of intensities that correspond to the degree of the importance of a cause. An effect is an intensity of reaction to any situation. The transformation matrix is formulated as $(\Lambda^i_{r1}(k, l) = (\frac{\partial x^i_{r1}(k,l)}{\partial t}); k = 1, ..., n; l = 1, ..., n)$. $(x^i_{r1}(k, k))$ is the vector of causes represented as a matrix of size $(k \times k)$. The diagonal entries are given as $(\Lambda^i_{r1}(k, k) = (\frac{\partial x^i_{r1}(k,k)}{\partial t}) = \|\ x^{init}(k, k) - x^i_{r1}(k, k)\ \|)$. $(x^{init}(k, k))$ is an initial matrix of causes of size $(k \times k)$ with cause levels representing an equilibrium. Then off-diagonal entries are given as $(\Lambda^i_{r1}(k,k) = (\frac{\partial x^i_{r1}(k,k)}{\partial t}) = E(x^{init}(k,l) - E(x^{init}(k,l))) \times E(x^i_{r1}(k,l) - E(x^i_{r1}(k,l))); k \neq l$). For a humanoid robot, the cause is always a demand from a human. Let (r1 = 1), meaning that the humanoid robot receives a first request from the buyer. Let the effect for the robot be designated by (y^j_{r1}). For the first human request the effect is formulated as $(y^j_{r1} = c^{eng})$ if $(y^i_{r1} = 0)$ else $(y^j_{r1} = y^i_{r1}(k))$ if $(y^i_{r1} \bigcap c^{eng})$. (c^{eng}) is the effect tensor programmed by the original engineer, $(c^{eng}(k) = \Lambda^{eng}(k) \otimes x^{eng}(k))$. If the buyer makes no more requests, $(r1 = 1)$, then $(y^{j+1}_{r1} = c^{eng})$ if $(\sum_{r1=1}^{N} y^i_{r1}(k) = 1)$. For all consecutive commands or requests, $(y^{j+1}_{r1} = y^i_{r1}(k); r1 = 2, \ldots, N)$ if $(y^i_{r1} \bigcap c^{eng} = 0; r1 = 2, \ldots, N)$. In Figure 2, $(C = c^{eng})$.

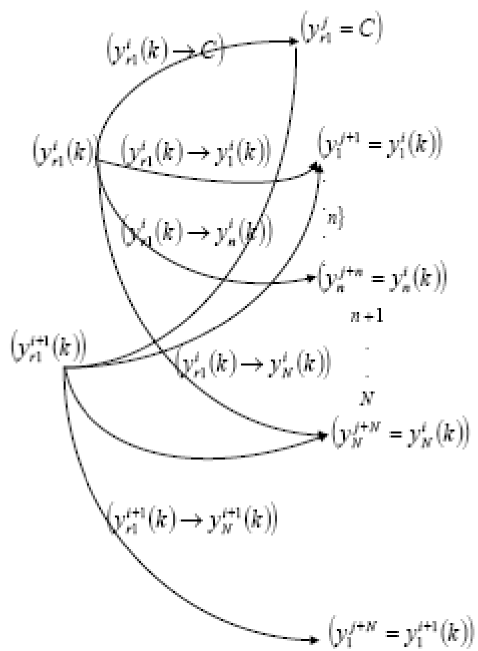


Figure 2. Network nodes as cause - n- effects

Figure 3, Shows a comparison between an individual effect tensor and a humanoid robot effect tensor.

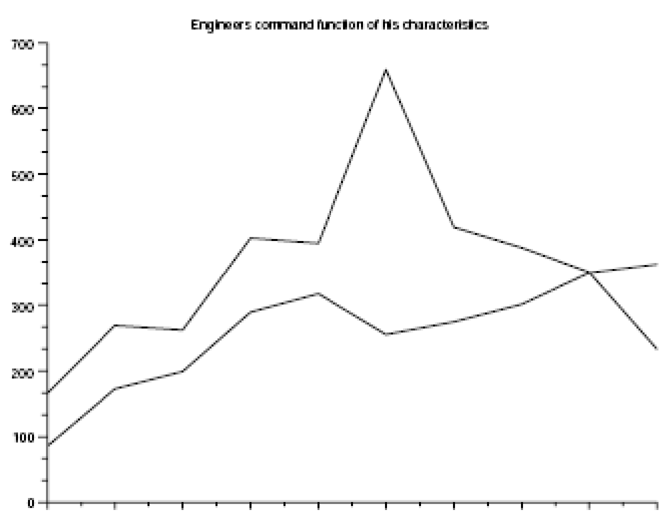


Figure 3. Comparison between an individual effect tensor and a humanoid robot effect tensor

In Figure 3, the x-axis indicates the number of causal factors, which in this case is ten. The causal factors are identified earlier. The y-axis represents the intensity of the effect tensor. Figure 3, is the result of a computer simulation. In the simulation model, each causal factor possesses an array of importance levels within [0,1] interval.(0) signifying that the causal factor has no importance. (1) signifies the highest level of importance. Importance means that a cause can produce an effect of a certain intensity. For example if a cause is an attribute such as patience, then in a very patient human (the patience is of importance level 1). The patient human reacts with much less stress to a situation. Here stress is an effect that has a low intensity. Each causal factor for an individual has an upper importance limit. The effect tensor for the individual and the humanoid robot is calculated as is described in the previous paragraph. In Figure 3, causal factor (6) which is curiosity produces the highest effect tensor intensity on the part of the individual, (this is the graph with the highest peak at level 700 points), while the same causal factor has the opposite effect tensor intensity (this is the graph with the highest peak at level 250 points)on the part of the humanoid robot. This is due to the fact that the humanoid robot only accepts the causal levels programmed by the original engineer. Causal factor (10) produces a higher intensity effect tensor on the part of the humanoid robot than the individual, (200 pts. vs 300 pts.). The individual and the humanoid robot do not converge to the same outcome. This reflects that the humanoid robot does not follow the intensity levels programmed by the original engineer once it gains more experience by interacting with humans through a cause-n-effect pathways.

3 Entropy

Entropy in the context of human - machine interaction is the interaction between an individual and a humanoid robot that results in new programming modules different from the initial program installed by the original engineer. The more the number of these programs the higher the entropy level. Analogy with Shannon Theorem is to consider an individual as a source. Source is an individual who emits signals in the form of an effect tensor that translates into an specific command or request, $(y^i_{r1}(k), \mu)$. $(\mu(y^i_{r1}(k)) = P(y^i_{r1}(k)))$ is the probability of an occurrence of an effect tensor, $(y^i_{r1}(k))$ given a vector of causes, $(x^i_{r1}(k))$. Interaction is a channel. A channel is an edge that emits signals in the form of effect tensors that are indicative of a command or some specific interaction, $(y^i_{r1}(k), \nu)$. $(\nu(y^i_{r1}(k)) = P(y^i_{r1}(k) \mid y^j_{r1}(k)))$ is the probability of an occurrence of a humanoid robot effect tensor, $(y^j_{r1}(k))$. This is a conditional probability. The output is a new module that allows the humanoid robot to perform new and different tasks. Source is ergodic since no two effect tensors are equivalent, $(y^i_{r1}(k) \neq y^i_{r2}(k))$. Entropy is measured by (H), where, $(H = -\sum_{r1=1}^{N} \mu \times lg(\mu) + \mu(c^{eng}) \times lg(\mu(c^{eng})) - \sum_{r1=1}^{N} \nu \times lg(\nu) + \nu(c^{eng}) \times lg(\nu(c^{eng})))$ where $(\mu = P(y^i_{r1}(k)))$, and $(\nu = P(y^j_{r1}(k)))$. The initial entropy is $(H_0 = -\mu(c^{eng}) \times lg(\mu(c^{eng})) - \nu(c^{eng}) \times lg(\nu(c^{eng})))$. $(\mu(c^{eng})$ is the probability of an occurrence of an effect tensor given the original engineer's cause vector, $(x^{(eng)}(k))$, and $(\nu(c^{eng})$ is the probability of an occurrence of an effect tensor $(y^j_{r1}(k))$. The initial entropy $(H_0 = 0)$ is equal to zero. It is assumed that entropy is positive and increasing $(H > 0)$ for subsequent human-machine interactions. In other words, entropy increases with time, $(H(t) < H(t + \Delta t))$. The schematics of dynamics of complexity and entropy are given in Figure 4.

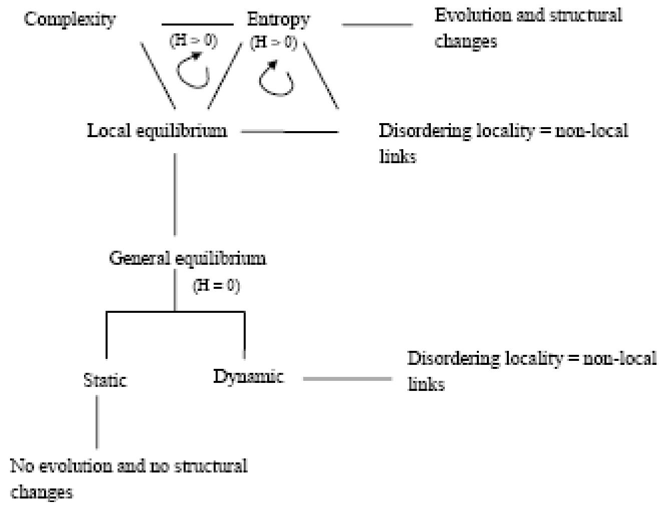


Figure 4. Schematics of complexity and entropy

In Figure 4, as humanoid robots come to contact with individuals they come into contact with a complex situation. The situation is complex because the contact is the result of causality. Therefore the dynamics of the contact are unpredictable and as such are inherently entropic. At this stage of the man-machine interaction the entropy is positive, ($H > 0$). It must be mentioned that the initial entropy is zero, since the robot is programmed by an engineer, and responds to his commands. Once the robot comes into contact with an individual, then the entropy becomes positive, ($H > 0$). The next stage is either a stable phase, or an unstable phase. A stable phase is the phase where the humanoid robot acquires a module or modules that correspond to the individual's causality. Therefore, the humanoid robot reacts positively to the tensor effects of the individual. This is considered as an evolution and an structural change of the robot. At this point the interaction between the individual and the robot is at local equilibrium. Local equilibrium occurs when the humanoid robot matches the individual's effect tensor, $(y^i_{r1}(k) = y^j_{r1}(k))$. If the individual does not add more modules to the robot, then a general equilibrium is reached, where ($H = 0$). This is an static situation where no evolution and no structural change can occur. An unstable phase occurs when the individual installs modules that change in time. An unstable phase can also occur if there exists disordering locality or non-local links. A disordering locality occurs when the humanoid robot comes into contact with a chance individual or unexpected connections. This leads to an addition of a random module onto a humanoid robot's system. For the humanoid robot an unstable phase implies evolution and structural changes. A graphical representation of a disordering locality is given in Figure 5. The link $((r, j+1))$ represents a disordering locality.

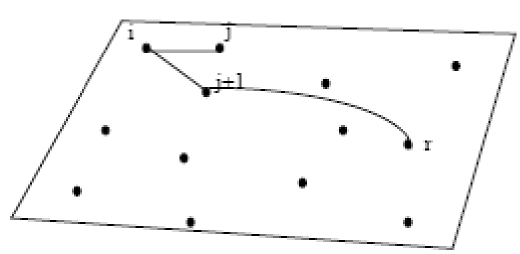


Figure 5. A disordering locality

Disordering locality can be formulated as $(y^r_{r1}(k) = \Lambda^r_{r1}(k)\otimes x^r_{r1}(k); r1 = 1, ..., N; r$ $1, ..., R)$. (r) stands for a random encounter, and (R) represents a finite maximum number of random encounters. $(\Lambda^r_{r1}(k))$ is the transformation matrix and is formulated as $(\Lambda^r_{r1}(k,l) = (\frac{\partial x^r_{r1}(k,l)}{\partial y^j_{r1}(k,l)}); k = 1, ..., n; l = 1, ..., n)$. (k) and (l) denote the number of causal factors. The diagonal entries of the transformation matrix $(\frac{\partial x^r_{r1}(k,k)}{\partial y^j_{r1}(k,k)})$ are formulated as $(\frac{\partial x^r_{r1}(k,k)}{\partial y^j_{r1}(k,k)} = \frac{||x^{init}(k,k)-x^r_{r1}(k,k)||}{||y^{j+1}_{r1}(k,k)-y^j_{r1}(k,k)||})$. The off-diagonal entries $(\frac{\partial x^r_{r1}(k,l)}{\partial y^j_{r1}(k,l)})$ where $(k \neq l)$ of the transformation matrix are given as $(\frac{\partial x^r_{r1}(k,l)}{\partial y^j_{r1}(k,l)} = \frac{E(x^{init}(k,l)-E(x^{init}(k,l)))\times E(x^r_{r1}(k,l)-E(x^r_{r1}(k,l)))}{E(y^{j+1}_{r1}(k,l)-E(y^{j+1}_{r1}(k,l)))\times E(y^j_{r1}(k,l)-E(y^j_{r1}(k,l)))})$. This formulation depicts the nature of disordering locality or non-local links that occur because an individual seeks to interact with an enhanced humanoid robot, $(y^{j+1}_{r1}(k))$. An enhanced humanoid robot is the one that possesses traits of a person other than the initial engineer. The transformation matrix $(\Lambda^r_{r1}(k))$ represents differential elements with respect to an enhanced humanoid robot. The existence of human-robot interaction in the context of several buyers, and particularly the occurrences of random encounters guarantee the existence of entropy. By the same reasoning this entropy is positive. The sole existence of entropy is a necessary and sufficient condition for evolution and structural changes of a humanoid robot. Entropy can be stable over time or during some periods of time. Entropy can be local or general as is seen in Figure 4. Long term entropy exists and the long term consequences are that a humanoid robot continues to evolve. Entropy inducing interactions are time asymmetric since no two different encounters are similar; and as such add complexity and structural changes. In general disordering localities create local entropy. This is the case whether the CDN is static or stochastic.

4 Causal Form Fluctuation Network (CFFN)

It is argued that a humanoid-robot becomes in all essence a multitude of individuals by accumulating programming modules from these individuals. Each module represents an individual. This is in terms of the individual's character, personality, beliefs, ideas, imagination, morals, and whatever elements are considered to be the soul of the individual. In fact human interaction with a humanoid-robot can be considered as a link that multiplies in number every time a humanoid-robot adds a module. The fundamental idea in this paper is that humanoid robots can acquire human traits simply by interacting with individuals not in a regulated monitored way, but in an unstructured or causal fashion. The connection between an individual and a humanoid robot is due to cause and effect on the part of the individual. Causality is considered to be a complex factor. By this it is meant that causality can be either static, transitive, or dialectic. Static causality produces static effects. Transcendental causality produces transitive effects. Dialectic causality produces dialectic effects.

The causality for a humanoid-robot is entirely different. Humanoid-robots have no causality. This is because they have no survival instincts. They posses no self-awareness, and no emotions. Machines age at a different scale, since the material they are made of is synthetic and not biological. Time does not have the same significance for machines as it has for humans. Machines evolve in a different way from humans, since they store data in various forms. They execute commands by comparing clusters of data. The effect for a humanoid-robot exclusively consists of executing a demand when an individual demands an action, answer a question, store an individual's experience as data, give an emergency response when there is an emergency request. A humanoid-robot is a problem solver when asked to find a solution to a problem at hand. It effectuates an analysis when there is a demand for analysis. If an individual tells a humanoid-robot an emotionally charged experience, hoping to receive sympathy, then the robot responds by executing a consoling sentence. When asked to analyse a situation by asking opinion, then a robot analyses the situation by comparing images and features, and their correlation, and looks for discrepancies. If an individual discusses instinctive responses to situations, and asks a robot for similar input, then the robot gives input by analysing entropy and disordering locality. An individual can discuss wisdom, and intelligence by giving examples, and ask for input, then the robot gives input by looking for the right module. In all these cases the robot simply reacts to the demands of an individual based on programmed modules. A robot does not make any decisions. It simply executes modules. Robots have no ideas of their own, and have no imagination. The three elements of decision making, ideas, and imagination are the fundamental differences between a human and a machine. Robots have no interpretation capabilities. They do not acquire wisdom (knowledge). Robots are incapable of prediction (intuition).

In order for a robot to evolve from just reacting to commands to actually forming a personality, an extension to the CDN network is proposed. Once the CDN is established, then the machine can analyse the causality. This is done by finding a path based on dialectic causality. Dialectic causality is causality that as a whole produces different forms (shapes). The criteria is to accept shapes with no sharp edges. Only shapes with round edges are accepted. Shapes with singularities can not be accepted unless it is possible to create a homomorphic shapes from the germ sets of these singularities. Example of singularities is a (Torus). In order to clarify the concept of dialectic causality, an example is given. Let the vector of causality $(x^i_{r1}(k))$, contain (6) factors, $(x^i_{r1}(k); k = 1, .., 6)$, $((x^i_{r1}(1), x^i_{r1}(2), x^i_{r1}(3), x^i_{r1}(4), x^i_{r1}(5), x^i_{r1}(6))$. Let the intensity of each factor be a value between (1), and (10), such that the causality vector is represented as a vector of intensities, (8,7,5,4,9,1). The highest intensity factor is factor number (6) with intensity value equal to (9). Based on the distance of other causal factor's intensities from the highest causal factor intensity, a path can be traced out. As is shown in Figure 6, this path has 3 lines and 2 arcs. It is considered that when two intensities are close they are connected by a line. When two densities are far from each other, then they are connected by an arc. An edge is considered to be sharp if it is a line. Since in this case there are 3 lines, and 2 arcs, then this set of causality is not an acceptable set. There are more sharp edges than round edges. Figure 6, demonstrates the path constructed by intensity levels of causality factors.

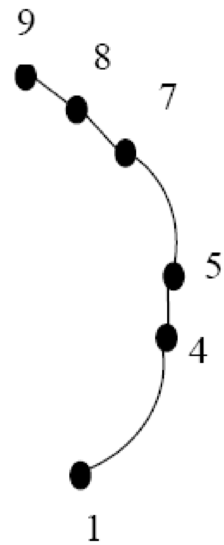


Figure 6. A rejected causality path

An example of an acceptable causality is when the same causality vector has the following intensity levels, (1,5,9,3,2,7). In this case there are 3 arcs and 2 lines in the path joining the causal factors. This set of causality is acceptable since the number of round edges is higher than the number of sharp edges. The path is considered to be round. Figure 7, demonstrates the causality path.

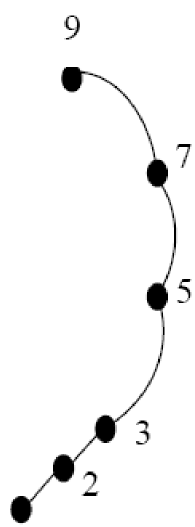


Figure 7. An accepted causality path

A set of accepted causality paths connected by hyper links make up the CFFN. Hyper links are links that connect the highest intensity factors in each of the acceptable paths. The highest intensity factors are used as entry and exit nodes of the hyper links because the highest point of each acceptable path, and thus easy to locate. Accepted causality paths connected by hyper links define the individuality of a robot. This means that the robot's effect or interaction is dictated by this set of accepted dialectic causalities.

5 Conclusion

The cause and effect dynamic network has the following advantages: 1) More human like humanoid robots, can be used for space explorations. A humanoid robot not only collects data, but also is able to interpret, analyse, imagine, and choose among solutions, and by doing so acquires wisdom. 2) Humanoid robots can be employed to perform difficult tasks. These robots would act as individuals would in difficult or dangerous situations, meaning assessing the positive and the negative, (+,-) aspects, guessing as what is the best way to solve the problem, not just relying on an algorithmic logic, but using also instinct, experience, wisdom acquired, and imagining the outcome by identifying and understanding the main elements of the situation. 3) Since humanoid robots learn by interacting with different types of personalities, and cultures, they can conserve civilizations that are towards extinction.

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