Robots that forget:
Improving Robot Situational Awareness By Purging Information

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***Abstract*— Autonomous robots are being designed to complete demanding tasks in complex, dynamic environments. Such environments require robots to comprehensively understand their situation, including the ability to develop and maintain human-level situation awareness. This paper proposes a novel approach to improving robot situational awareness based on providing a mechanism for forgetting information. Robots are inundated with data, which are often erroneous, out of date, or irrelevant. The proposed approach may permit robots to rid themselves of onerous knowledge, improve information recall, and process data beneficial for situational awareness.**

I. Introduction

While tremendous success has been achieved in the field of Artificial Intelligence, robots are still ill-equipped to detect, recognize, and act upon many of the small but critical details within the environment that greatly impact the probability of successful task completion. Much of this inability may originate from robots lacking human-level Situational Awareness (SA) [1]. This paper aims to increase robotic SA capabilities by taking inspiration from human biology and psychology and channeling it into a mechanism to purge unnecessary and erroneous data from robots' memory, making mission critical information easier and faster to retrieve and utilize.

Robots in complex and dynamic environments are often inundated with copious volumes of data. Sensors, algorithms, and task information can easily congest a robot's databases. To generate and maintain SA, robots must quickly parse, process, and categorize available data to gain a comprehensive understanding of the current situation and make well informed action selections. One way to aid robots is to rid them of unimportant, out of date, or erroneous information. Forgetting[1], the inability to recall information, has been recognized as beneficial to machine-learning, particularly case-based reasoning [2]. In particular domains, even random forgetting has been found to improve performance [2]. Within some machine learning domains, even correct data can sometimes reduce performance [3]. This paper proposes that mechanisms of human forgetting can be applied to robotics in order to reduce their informational burden. Care is required when introducing these concepts, as they could result in constraints or limit design possibilities.

This paper begins by defining Situation Awareness (SA) and describing how purging information may benefit robotics. Next, a short review of the two main theories of forgetting within human short-term memory is provided [4]. Three relevant journal papers are then reviewed. Models presented in these articles are classified according to the presented theories. Concluding this paper, the proposed approach to robotic forgetting that was designed to aid robots in generating and maintaining human-level SA is presented.

[1]To avoid confusion with the family of terms: Trace-Decay, Time-Based Decay, and Decay, the phrase "Memory Decay" will not be used by this paper. The term Forgetting will be used in its place.

TABLE I
Levels of Human Situational Awareness [11]

Level 1	**Perception of the environment** Level 1 SA involves the acquisition of raw sensory data from the environment. This data may include the location of nearby items, the status condition of teammates and adversaries, and environmental characteristics.
Level 2	**Understanding of the current situation** Level 2 consists of merging data from Level 1 to form an understanding of the current situation in the environment. The concepts of Level 2 SA will be composite, incorporating relations between multiple Level 1 SA data items and possibly other Level 2 data. This may include detecting patterns in the data and relating them to domain specific knowledge.
Level 3	**Predict future events and actions** Level 3 combines both Level 1 and Level 2 constructs to predict future states of the environment and possible actions to undertake. Known dynamics and tendencies of objects within the environment are often utilized to gain an understanding of the evolution of the environment and possible consequences of actions.

II. How Forgetting May Benefit SA

Situation awareness (SA), a concept that has received considerable attention in the human factors community, considers humans' ability to understand and make decisions within complex dynamic environments [5], [6], [7]. Endsley defines SA as

> "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future [8]."

Endsley's definition is used in this paper, although many other definitions exist [9], [10]. Endsley decomposed SA into three levels [11], which are described in Table I.

Before a system can be implemented to improve a robot's SA, the specific benefits to SA must be determined. Each level of SA possesses different attributes that can be affected differently by the addition of a forgetting mechanism. Level 1 concepts are generally atomic, consisting of either a set of similar raw data items (e.g. logged sensor readings) or singular items receiving a continuous stream of updates (e.g. bump sensor status). Purging may have an insignificant impact on items that receive a constant set of updates, but may prune data from raw data sets.

Level 2 SA may benefit the most from forgetting. Composite objects, Level 2 constructs are the melding of multi-modal information to form higher level representations of possibly highly dynamic constructs. Purging may realize two separate benefits. First, Level 2 items have relations to Level 1 items. When these lower level items are modified or removed, the Level 2 item may be modified. Unnecessary relations and subcomponents may be removed or the entire item may be deleted. Second, the entire item may be deemed unnecessary and removed.

Level 3 concepts may be affected in many of the same ways as Level 2 concepts. The difference lies in the effects on the system. Level 3 concepts predict the effects of actions and the evolution of the environment. These items may already be highly dynamic and possess a short life-span. Additionally, Level 3 concepts may be less likely to be a subcomponent to a higher item. As a result, the effects of forgetting a Level 3 concept may be slightly smaller than that of Level 2 items.

III. Mechanics of Human Forgetting

A long standing debate has raged regarding the form and mechanics of human forgetting [12]. Two prominent theories exist, time-based decay and similarity-based interference, which appear to stand in stark contrast to one another [4]. The first, subscribes to the belief that the passage of time directly degrades items within memory, while the later postulates that accumulation of inter-item interference prevents items from being successfully recalled. Numerous models of each theory have been developed that appear to accurately model empirical evidence, but the developed analyses and their models have also sparked controversy [4], [13], [14], [15], [16]. The complexity of psychological testing of humans has driven a serious debate over the possibility of diverse arrays of confounds that can cloud the interpretations of the results [4], [17], [18], [16]. Further complicating matters, it has been postulated that some psychologists have misread and misinterpreted previous findings, resulting in the dismissal of valid ideas and the reluctance to accept new theories [16], [14].

These debates are further heightened by the multiple forms of human memory, which can be partitioned into two major categories [19]. Procedural memory is highly stable, non-symbolic knowledge without a truth value. It simply forms stimulus-response pairings. Conversely, declarative memory is "knowledge that can be introspectively reasoned over without any overt behavioral response" [19]. Declarative memory groups two separate but parallel memory types, episodic memory and semantic memory [20]. Episodic memory maintains a collection of individual episodes and events, including temporal-spatial relations. Semantic memory is a non-instance based memory involving "the acquisition, retention, and utilization of skills and knowledge that have to do with the world" [20]. Some models and analyses of forgetting are strongly dependent on a particular form of memory. Altmann and Gray [21] stated that their functional decay model relies heavily on episodic memory representations, although Sims and Gray [15] questioned this dependence.

Item representation, which may be influenced by types of memory, adds additional uncertainty regarding the nature of forgetting. Presently, at least two forms of storage have been considered within short-term memory, whole item storage and the binding of features [4]. Models of both decay and interference based forgetting have been developed utilizing both short-term storage approaches.

A. Time-based Decay

Time-based decay is the intuitive concept that items within short-term memory deteriorate and eventually disappear due to the effects of time [4]. At perception, items are encoded in memory at a particular activation level, dictating ease of retrieval. As time passes, this activation level decreases, increasing the difficulty of item retrieval. To combat these effects, the memory system performs a refreshing strategy called rehearsal [18]. During this process, memory items are recalled in order to strengthening their activation levels [18]. As shown in Figure 1, the activation level of a memory item may undergo three stages [22]. *Strengthening* involves memory rapidly recalling the item to boost its activation level. The middle stage, *Use*, involves memory recalling a memory item to complete a task. During this period, recall provides a boost to the item's activation level, but not at a rate to fully counteract decay. In the final stage, *Disuse*, the item is no longer used and the activation slowly decays.

In 1885, Ebbinghaus [23] presented the original forgetting curve, a logarithmic function that predicts memory [12], which can be estimated with a power function [24]. A commonly used equation for modeling time-based decay, Equation 1, can be found in the ACT-R (Adaptive Control of Thought - Rational) cognitive architecture [25]. This function calculates the item's activation in memory at a particular point in time. β represents the item's initial activation level, n is the number of times the item has been recalled or perceived, d is the rate of decay, $\epsilon_1 + \epsilon_2$ represent noise terms, and Σ(WS) determines the activation boost due the item's similarities to the current context.

$$\begin{gathered} a = b + \sum_i (W_i S_i) + \varepsilon_1 + \varepsilon_2 \\ b = \beta + ln(\sum_{j=1}^{n} t_j^{-d}) \end{gathered} \tag{1}$$

While mathematical models of time-based decay exist [13], there are no generally agreed upon biological mechanisms to support time-based decay, although several mechanisms have been proposed [4]. One suggestion postulates that neurons forming an item in memory fall out of synchrony, continually increasing the difficultly of retrieval [26]. A

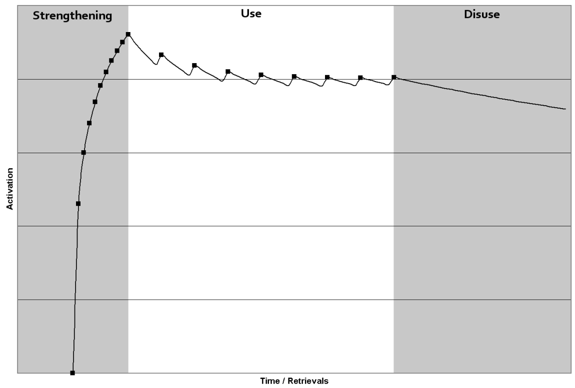

Fig. 1. Time-Based Decay (adapted from [22])

second states items do not deteriorate, but their probability of receiving memory's focus of attention wanes, making the item harder to recall [4].

Both psychological-based and neurological-based empirical evidence has been collected in order to verify time-based decay, but alternate explanations exist for many of the discovered trends [4]. These alternate explanations have been used as support for interference-based forgetting [27].

B. Similarity-based Interference

Similarity-based interference, the current dominant account of forgetting [4] has a long and storied history [16]. While proponents of interference admit that forgetting is correlated with time, they believe the true causes of failed recall are processes and activities that occur during a time span [18]. Unlike decay theory, interference predicts failed recall results from inter-item competition for the memory system's focus of attention [12]. Interference-based forgetting is a complex theory involving many forms of competition between items. Competition can be affected by item encoding strength, the number of items, the similarity between items, and the phase of learning and recall (encoding, storage, and retrieval) [4]. Two common methods exist for partitioning the theories of interference, the point of interference (encoding and output) [27] and the age of affected items (retroactive interference and proactive interference) [4]. The former compares Encoding Interference (EI) with Output Interference (OI) while the later contrasts Retroactive Interference (RI) with Proactive Interference (PI). Each form of interference exhibits different behaviors and many models of forgetting promote one over the other. As presented in [4], the remainder of this section will present the differences between RI and PI.

1) Proactive Interference: PI effects entail existing memory items decreasing the encoding strength of new items and increasing the difficult of recalling the new items [4]. PI is often associated with cue-overload, a phenomena where items associated with the same or similar cues interfere with each other [16]. When a new item is initially perceived, the effects of PI may be small but will increase with time. It is speculated that items previously associated with a cue are unintentionally recalled during the new item's retention period resulting in interference [16].

2) Retroactive Interference: RI describes the phenomena where new memory items interfere with existing items [4]. While an item of debate, there appears to be a RI gradient immediately following the perception of an item. Some believe that after memory trace creation, a consolidation process begins that strengthens the item. As items consolidate, they become more resistant to interference and the effects of RI decreases [16].

Skaggs [28] has posited that RI effects actually arise from two separate processes, similarity and mental exertion. Receiving grater acceptance, similarity effects dictate that increased similarity between items results in greater RI [4]. Mental exertion provides non-similarity based RI. During an item's consolidate process, the presence of mental exertion of any form will adversely affect the consolidation process and the item's final encoding strength [16].

IV. Review of Assigned Literature

This section provides an in-depth review of three journal articles that demonstrate empirical results for both modes of forgetting. For each paper, the models used to predict forgetting will be classified into the above categories.

A. Functional Decay of Memory for Tasks [22]

This paper presents the concept of functional decay, a hybrid model of forgetting that combines both time-based decay and interference effects. After an initial description of functional decay, the paper presents three human participant experiments that demonstrate within-run slowing, a phenomena where a decline in task performance results from increasing recall difficulty. The presence of within-run slowing suggests the presence of functional decay. The first experiment investigated the difference in magnitude of within-run slowing when memory is required and when memory is optional for a task-switching task. The second experiment reduced the predictability of the task switching cue in order to test the affects of anticipation on within-run slowing. The third experiment performed a modified version of experiment 6 from [29] to verify that within-run slowing is not isolated to only the task paradigm used in the first two experiments. The paper concludes by discussing a model of functional decay and its ability to explain several otherwise unintuitive empirical findings in recent literature.

The presented functional decay model, which is based on an episodic instance-based representation [21], uses a simplified ACT-R activation equation (Equation 2) to reduce a task cue's ability to be recalled as time progresses. When a task cue is observed, a new memory trace is created, irrespective of whether the cue represents the same or a new task. A more elaborate description of decay is presented in which an item in memory has three stages. Stages two and three, use and disuse, are often found in the literature. Strengthening, stage one, represents a rapid series of item recalling to boost the item's activation level from zero (or its presently decayed value at re-perception) to its maximum value.

$$Activation = ln(\frac{ItemRecallCount}{\sqrt{LifetimeOfItem}}) \quad (2)$$

Interference is present in functional decay due to a task cue's interaction with subsequent cues to be recalled. According to the theory, there is a minimum difference that must be maintained for the memory system to correctly recall the latest cue instead of becoming confused or selecting an incorrect item. To prevent incorrect recall due to interference, the memory system adapts its decay rate to achieve the minimum separation of activation values required for correct recall. Under this model, the memory system predicts the arrival of new items to be encoded and adjusts the rate of decay accordingly.

It is unclear how this model applies to a more general memory intensive task. As described, one item (the task cue) needs to be remembered and subsequently recalled at any time. As a new item appears, the previous item is to be discarded. The paper does not describe how this model would permit remembering multiple items concurrently or how they could be disambiguated.

B. Time Does Not Cause Forgetting in Short-Term Serial Recall [27]

This paper presents evidence that output interference may be the primary factor in forgetting during serial recall. After a comparison between time-based and event-based models of forgetting, this paper describes a simulation comparing time-based, output interference based, and decreasing encoding strength based models. With a minor modification to allow for simulation of event-based forgetting, the SIMPLE (Scale Invariant Memory, Perception, and Learning) model [30] was used to compare a number of serial recall curves, demonstrating that event-based models may better reflect the effects of primacy. The paper presents several classes of experiments whose data had previously been used to bolster the concept of time-based decay. For each set of experiments, the paper described alternate explanations that did not require time-based decay. Two experiments concluded the paper, the first asked human participants to perform a serial recall task while pacing the rate of their responses. The second asked participants to perform a serial recall task, but to responded verbally instead of typing their answers and to repeat a suppressor word multiple times instead of maintaining an absolute response speed. As the experimental results did not demonstrate effects of output time and the event-based model provided more accurate predictions, the paper concluded that output interference has a greater effect on forgetting than time.

Despite contrasting time-based and event-based models of forgetting, trace decay is not directly addressed in the paper's experiments. Instead, this paper elected to compare temporal distinctiveness models to output interference. While time is a factor, distinctiveness models can be considered models of interference as the absolute passage of time does not have a direct effect on memory and forgetting. Instead, the relative times between item observations determine item selection. As a result, time can be considered another category where items can interfere, with the exception that the time "category" is constantly gaining new values.

The event-based model in this paper represents several sources of forgetting including encoding interference, recall interference, and variable encoding strength. Except when output interference was modeled as the event-based alternative in the simulation of forgetting, the exact sources of forgetting are relatively ignored. The experimental results are analyzed from the perspective that when the trace decay model does not fit, then event-based models must be correct.

C. The Two-Second Decay Hypothesis in Verbal Working Memory [13]

This paper refutes the notion that verbal memory has a decay time of approximately two seconds. The historical rational for this two second belief is presented as the result of a misinterpretation of the model by Schweickert and Boruff [31]. A broad body of empirical data is presented to both refute previous findings and identify evidence that verbal memory lasts longer than two seconds. The paper develops a mathematical model to calculate a possible lower-bound on the time for verbal memory to decay.

The paper begins with a diverse array of auditory and verbal memory data showing items in memory can decay within a time period of one hundred fifty milliseconds to twenty seconds. Reasons are then presented regarding why these results are misleading, testing something other than verbal memory, or actually strengthen the argument for decay times greater than two seconds.

A model derived from the EPIC (Executive-Process/Interactive Control) model [32] is presented that accounts for forgetting solely through time-based trace decay. During the model's presentation, a description of the Schweickert and Boruff model [31] provides a valuable lesson regarding how misinterpretation of models or results can have significant and long lasting consequences. The paper's model of forgetting has two versions, with and without rehearsal effects. Both versions assume items decay independently and that the product of each item's conditional recall probability approximates the probability of complete list recall. Only arguments of list length, inter-item presentation delay, and the delay between presentation and recall are used. No interference effects are modeled. A probability density function (PDF) is used to calculate individual item probabilities. The selection of PDF can have profound effects on the modeling results. The paper shows that while the ability to correctly recall an entire list may fade in two seconds, the laws of probability dictate that each item comprising the list must remain, on average, longer than the lifetime of the complete list. This effect becomes more severe as the list length increases.

It appears that something is missing from this paper's argument for two reasons. First, the paper considers only a pure trace decay model, but states that other factors probably exist. It is unclear if these other factors would always be present in some form, thus increasing the short-term memory decay rate. Second, if interference actually is the dominant factor in forgetting, then these results may not apply to many memory related tasks.

V. Proposed Robotic Forgetting Mechanism

This paper will now propose a new approach to implementing forgetting within robots in order to improve the generation and maintenance of human-level SA. The proposed method is unique in that it is designed specifically for robots and incorporates a breadth of mechanisms and theories. This new mechanism can not realize robotic SA by itself but may form an integral component in a suite of mechanisms that together achieve human-level SA.

Through the years, strong evidence has been found to both support and refute the two leading theories of forgetting, time-based decay and interference [4]. Some research has posited that forgetting is a combination of both theories and their subcomponents [4], [16], [15], [21]. Reflecting on the complexity of the human mind and cognition, it is unlikely that the full dynamic of forgetting can be realized from one parsimonious mechanism. Several researchers have developed models of forgetting that incorporate multiple forgetting methods [13]. Others that stand by one mechanism, have admitted that multiple mechanisms may contribute to forgetting, just to a lesser extent [16].

The proposed approach combines time-based decay, effects of mental load, input interference, and output interference. Through the unique collection of mechanisms in the proposed forgetting system, the approach may be highly amenable to the varied demands of robotic systems. By modifying constants, and the relative importance of the mechanisms, the system may be tailored to specific domains and tasks.

This section proceeds as follows, first a description of the system's properties are explored. Next, the incorporation of time-based decay is explained. Mental load's impact on the system is then described. Input interference affects are then presented, followed by the influence of output interference. Finally, the integration of all of the components is explained. In the equations that follow, small c's represent constant scaling factors and offsets.

A. Properties

A number of properties need to be described before the system's implementation is presented. Few restrictions are placed on robots using this forgetting mechanism, but it is assumed that data structures consisting of lower level data groupings exist. Kira and Arkin [2] previously implemented a forgetting mechanism into a case-based reasoning system for a simulated mobile robot. Each case was implemented as a fixed collection of scalar values representing internal parameters and traversability of areas directly adjacent to the robot [33]. Kira and Arkin's cases were fixed data structures but many systems may use variable size constructs. Robots generating Level 2 and Level 3 SA may require a binding facility [34] that combines low-level information into composite representations of higher level constructs. These new constructs may be variable in size. To handle these representations, the proposed system follows the models of Nairne [18] and Oberauer [17] by calculating activation levels at the feature level, rather than the item level. When an item's activation level requires updating, all of the item's features' activation levels are updated and combined to form the item's new activation. Specifying features is task and domain specific.

It has been posited that working memory operates on a number of levels, implying different item recall difficulties [4]. Oberauer's [17] model presents three levels of focus, "the activated part of long-term memory", "the region of direct access", and "the focus of attention". The first represents activated long-term memory currently residing in working memory. The second represents highly activated items that can be directly accessed, while the third represents the item currently under focus. While any number of focus levels could be used by the proposed system, it is intended for the system to have only two, as the level specifying the current item may be unnecessary for robots. Unlike in Oberauer's model, the levels in the proposed system act as filters, reducing the number of items to be considered. If no items at a given level are acceptable, the system can then search the next. At the lower level, items may have only a small probability of being recalled, but they will provide structured noise, facilitating the forgetting process [4].

B. Time-Based Decay

While time-based decay theory previously fell out of favor [16], decay has recently regained a significant amount of support [14], [16]. Time-based decay's durability and recent resurgence provides strong evidence that it has an affect on forgetting.

While multiple forms for the algorithmic process of forgetting have been proposed that exhibit a decreasing proportional rate of decay [16], the power law family of equations, which has been posited to best characterize forgetting [16], [35], [36], will be used. A commonly cited equation is the ACT-R base activation equation, Equation 1, and its many simplified forms (e.g. Equation 2). Pavlik and Anderson [37] modified Equation 1 to incorporate the item's activation level at each time of retrieval [15]. This modification realizes the spacing effect of short-term memory and better models within-run slowing. The Pavlik and Anderson equation, Equation 3, will be used to model time-based decay. Depending on the robot, β can be set to a fixed value or a dynamically generated value, such as a belief level [38]. a_{fj} represents the feature's activation level at the item's jth retrieval and $a_{f_{base}}$ represents the feature's base activation. r_j is the span of time since the item's jth recall.

$$\begin{aligned} d_{fj} &= c_1 e^{a_{fj}} + c_2 \\ a_{f_{base}} &= \beta + ln(\sum_{j=1}^{J_f} r_j^{-d_{fj}}) \end{aligned} \tag{3}$$

C. Encoding Interference

Two forms of encoding interference are incorporated into the proposed forgetting approach, mental exertion and similarity-based encoding interference. Mental overload has been incorporated by different means than similarity-based encoding interference and will be described in Section V-D.

Many complex domains require robots to possess diverse arrays of knowledge to achieve high performance levels. Developing SA requires acquiring data from many sources, which can quickly strain robotic memory capacities. Limits in raw storage and computational restrictions may constrain SA generation. Incorporating encoding interference may aid robots in maintaining breadth of knowledge without purging or ignoring critical information.

The proposed encoding interference is modeled after ACT-R's encoding interference [25]. As the number of items possessing a particular feature increase, the probability that any one of those items being the next item recalled when that feature is required, will decrease. Equation 4 generates a scaling factor based on the number of items possessing a particular feature. S_{EI} generates both RI and PI.

$$S_{EI_f} = \frac{1}{NumberItemsWithFeatureF} \tag{4}$$

D. Mental Exertion

It has been posited that memory items may consolidate or become more durable after they are perceived. Mental exertion during this consolidation period can increase the likelihood that the item will be forgotten [16]. This form of RI may be beneficial to robots operating in complex and dynamic environments as it may foster a form of focused attention. When a robot is under a heavy computational load, the addition of more memory items may slow comprehension and subsequently reduce SA. By incorporating RI through mental exertion, irrelevant details may be encoded at reduced strengths and quickly removed. Conversely, important items will rapidly be recalled, boosting their encoding strength and negating the effects of mental exertion.

The effects of mental load have been incorporated into the proposed system by generating a scaling factor, S_{ME}, that modifies an item's base activation level. S_{ME} is computed by taking the integral of mental exertion experienced by the robot during a time-window near the item's perception, see Equation 5. In this equation, *t1* and *t2* represent the bounds of the time-window. While in the time-window, the robot updates S_{ME} each time the item's encoding level is required.

$$S_{ME} = c_3 \int_{t1}^{t2} MentalExertion\, dt \tag{5}$$

E. Output Interference

When robots are operating within complex and dynamic domains, there will often be periods of low computational demand followed by intervals of high computational load. Output interference is added to the proposed forgetting mechanism to decrease the volume of data that must be processed during these high load periods. As the robot makes decisions, the effects of output interference increase, systematically removing irrelevant and possibly erroneous information as the rate of decision making increases. The greatest benefit from output interference may be seen in domains where each subsequent decision or action increases the importance of correct decision making while reducing the available response time.

Based on the model of Lewandowsky, Duncan, and Brown [27], output interference has been added to the system through a parameter (S_{OI}) that scales the current feature's activation level by an amount dependent on the number and timing of previous item recalls. Equation 6 is used to update S_{OI} and was inspired by ACT-R's base activation function (Equation 1). Unlike the conditions where Lewandowsky et al.'s model was evaluated, the robotic system may be required to operate for long periods of time, making a significant number of recalls. With the original model, output interference never decreased and eventually the robot would be unable to continue. A power law decay was added to the magnitude of the output interference scaling factor so interference effects would wane during periods of infrequent recall.

$$S_{OI} = c_4^{(c_5 + ln(\sum_{j=1}^{J} t_j^{-c_6}))} \tag{6}$$

F. Combine

This subsection explains how the above components are integrated into one coherent system. Equation 7 combines β (feature base activation), with the effects of trace-decay, mental exertion, encoding interference, and output interference into an activation level for each feature of each item in memory. Equation 8 combines an item's features into a single activation level from a weighted sum of two competing properties. The first is that an item with more features may be more stable and have a higher probability of being correct. The second uses the average feature activation level. This is required because otherwise an item with few but strongly activated features may get overshadowed by items with large numbers of features with low activation.

$$a_f = S_{OI} S_{ME_f} S_{EI_f} (\beta + ln(\sum_{j=1}^{J_f} r_{fj}^{-d_{fj}})) + \varepsilon \tag{7}$$

$$a_{Item} = c_7 \bar{F} + c_8 \sum_{f}^{F} a_f \tag{8}$$

Once the item activation level is computed, the item's focus level is updated via the procedure in Figure 2. When an item has not exceeded any thresholds, it is deleted. By sorting items into the focus levels, the system provides data filters possibly reducing the robot's search space for the next item retrieval. In addition to deleting items, when the memory items have been implemented with variable data structures,

Fig. 2. Placing items in focus levels

```
foreach item
 if(ItemActivation >= Level1Threshold)
  ItemFocusLevel = FocusLevel1
 elseif(ItemActivation >= Level2Threshold)
  ItemFocusLevel = FocusLevel2
 else
  delete Item
end foreach
```

features that have an activation level below a threshold will be removed from the item.

While not directly part of the system, robots using this mechanism can utilize rehearsal strategies to modify the activation values of memory items. By periodically recalling particular items, the system will increase their activation levels, potentially increasing thier focus levels and preventing the items from being deleted.

In complex and dynamic domains, robots must process large volumes of diverse data. Through the human forgetting inspired filtering and purging provided by the proposed system, it is believed that robots may be better equipped to generate and maintain SA.

VI. Conclusions and Future Work

In recent years, the understanding of short-term memory has advanced considerably, introducing new theories and updating outdated thinking [4]. This paper proposed a new approach to developing human-level SA within robots by combining the forgetting capabilities of human short-term memory with existing and future robotic technologies. Before human-level SA can be realized, may advances will be required, but forgetting may play a significant role by ridding the system of erroneous, outdated, and useless information.

Many avenues of future work exist for incorporating forgetting. Empirical evidence of the algorithm improving SA will be required to verify its effectiveness and determine the relative importance of each mechanism. Item and feature activation levels may aid other systems in a robot. Tighter integration with belief states may be possible along with using the activation level to modify item selection probability. Short-term memory forgetting inspired this approach but long-term memory mechanisms may also aid the generation of human-level SA in robots.

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