TL-PC: An Interpretable Causal Relationship Networks on Older Adults Fall Influence Factors

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***Abstract*—Identifying the internal relationships in the data is the basis of data analysis and prediction. Traditional statistics methods focus on testing the correlation of variables pairwise. However, the correlation has rather limited performance on real causal influence. In this paper, we focus on an interpretable and visible approach to detect causal relationship networks in order to study risk factors of older adult falls. Learning the skeleton of the network is challenging since it is hard to mine indirect relationships. Variables could have dependence given other variables. Furthermore, orienting appropriate direction is tough because real-world data may include hidden information. Researchers cannot control it like a simulated data set. Here we propose a method based on the Bayesian causal relationship, which we call the Time Logic PC algorithm (TL-PC). We use the TL-PC on the older adults fall application and show the explainable and reliable time logical causal relationships.**

***Index Terms*—Causal relationship networks, Conditional independence, Time logic, Interpretable, Dynamic performance**

I. INTRODUCTION

Falls have been detected as one of the most important causes of death in older adults. Approximately 9,500 deaths in older Americans are associated with falls each year [1]. Furthermore, falls are also one of the most common causes of accidental injuries among seniors. It is reported by one-third of people over age 65 each year [2]. Therefore, identifying the risk of falls and taking care of older adults with high risk is very important. To recognize the risk, it is significant to dig out the relationships behind falls data and understand these relationships among explanatory variables.

Domain researchers usually use statistical analysis tests to detect the relationship between their variables, such as using the t-test to test if they are correlated. However, traditional statistical tests are very limited on visibility, interpretation, efficiency, and effectiveness. The model-based statistical method is very sensitive to the model. It is important to use the specific model with specific data, which will cause more uncertainty and cost to researchers. On the other hand, researchers who do not have a strong background in statistics hardly survive from the results which only comes with numbers when they try to understand and explain them. An interpretable method is much needed to help researches dig out causes of older adults falls.

Machine learning models, as is well known, are used to do prediction combining with different domain data set. Most machine learning models follow data-driven pattern which means case sensitive [23]. Compared with traditional model-based statistics methods, the data-driven characteristic can avoid uncertain errors from the inappropriate model selection. The elementary goal of these data-driven methods is pursuing higher precision of the prediction model. Like, the feature selection technic is one of the most popular approaches to realize this goal [20]. However, there is no evidence showing that the best prediction features from machine learning models are also comprehensible features for domain researchers. One of the biggest problems is that prediction results from algorithms are not highly accessible to domain researchers, especially in health science. For instance, doctors won't make a prescription following the prediction of unfamiliar machine learning models. In this case, understanding the hidden relationships between features is in higher demand than simply doing prediction by applying machine learning models. We note that a good performance of prediction is not equal to the real causal relationship in the domain. For example, we know that people who smoke often drink. Based on this rule, smoking and drinking are correlative variables, whereas smoking is not the direct reason for alcoholism and drinking also does not cause smoking. There is no causal relationship between smoking and alcoholism. In this paper, our goal is to design and implement a machine learning algorithm that will not only predict future phenomena with high precision but also provide an approach for domain researchers to mine in-depth information on complex interactions.

Using structured networks is a way to perform much more visible result reports than statistical tests. These types of reports are more readable and comprehensible. On the other hand, there always exists interactions between multiple variables in real-world data. To diagnose and consider relationships between numerous features sequentially, we use conditional independent test, which follows the Bayesian rule, a powerful nonparametric method detecting and revealing causal relationships between variables [21], but considers the effects from previous variables instead of traditional independent test.

In this paper, we propose Time Logic PC algorithm (TL-PC), a new application framework of Bayesian causal relationship algorithm, as a combination of the traditional statistical method and the modern machine learning way. We provide data-driven patterns and Bayesian rule from traditional statistics together to address current limitations. The motivation of TL-PC is to provide a visible result to help domain researchers understand their data and mine more deeply information from the data in an efficient way. As shown in Fig. 1(c), TL-PC provides a case sensitive processing learning skeleton structure from data sequentially. And then applying v-structure and time logic technique to orient the direction of each adjacent edge. These directed edges represent causal relationships between each pair of nodes. With the time logic, the model can provide more reliable causal relations than the original Peter and Clark (PC) algorithm.

Moreover, our method is competitive on dynamic performance. Fig. 1(d) shows very few differences between the number of relations at different thresholds. Furthermore, the number of links always increases when the threshold goes up, which means that the previous links are steady and will not disappear if we use a higher significance level. So the relations detected by our method are robust and reliable. It is possible to investigate dynamic performance with a different threshold to identify strong and weak relations. As shown in Figure 1(a) and 1(b), we propose an ideal relationship structure among chronic pain, gait, and falls. Then we evaluate TL-PC with real-world data (see Fig. 1(b) for data collection) to test the conceptual model of chronic and gait effect on falls.

The major contributions are shown as follows.

- Applying TL-PC algorithm, a method based on conditional correlation test, to detect the causal relationship between variables from a real-world data set. The time order rule is also applied as an adjustment factor in the model.
- Comprehensive results with figures that visualize the performances, which help identify causal relationships between variables. Since the results generated by the TL-PC algorithm based on the conditional independent test are more convincible than traditional pairwise statistics methods.
- A way to improve efficiency and effectivity. Our application model can provide precise results with less computational cost.

II. Time Logic PC Algorithm

Both traditional statistical methods and data-driven prediction methods limit on dig out causal relations. To deal with this problem, a combination algorithm, Peter and Clark (PC), is proposed [4]. The PC applies conditional independence(CI) test which is from traditional statistics on data-driven iteration idea. The algorithm can learn information from an individual sample through statistics CI test. Furthermore, the directed acyclic graph (DAG) is used to perform the causal relations, which is provided in an easy understanding way. The PC algorithm, a computationally feasible and fast approach to solve sparse problems with a mass of variables, has high computational efficiency with DAG automatically [22].

Based on the original PC algorithm [4], we propose the time logic PC (TL-PC) method which considers time order when generating the causal relationship networks. Our networks result is more interpretable and reliable than the original PC. A stable and time logical result is very important for researchers, especially for health science, since participants always have some uncontrolled initial features, like gender, when they join the experiment. In this case, time becomes significant in causal relations.

To detect causal structure, we have to consider parent variables in each test step. The PC algorithm updates the joint distribution of the variables using Bayesian conditional probability [4]. Instead of the normal independence test, conditional independence test is applied to decide whether the pair of variables are dependent. If the conditional probability satisfies the Eq.(1), the variable A and B are conditionally independent given C.

$$P(A, B|C) = P(A|C) \cdot P(B|C) \tag{1}$$

There are two main steps in the TL-PC algorithm, including learning skeleton and edge orientation. In the first step, the TL-PC will follow the original PC [4] return an undirected graph with all vertices and edges. All the directions will be given in the second step. The CI test is used to learn skeleton, while other techniques, v-structure and time logic, is used to orientate edges. Suppose graph G = (V, E) is an undirected graph which has V vertices and E edges where $\{$all vertices of E$\} \subseteq$ V.

Definition 1. ***Adjacency [3]:*** *Vertex A and B are adjacent in graph G if (A, B) or (B, A)$\in$ E and (A, B) or (B, A) $\in$ G, called adj(A, G).*

For each pair of (A, B) or (B, A) given C, there could be four different v-structures, 1)$A \rightarrow C \rightarrow B$, 2)$B \rightarrow C \rightarrow A$, 3)$A \rightarrow C \leftarrow B$, and 4)$A \leftarrow C \rightarrow B$. These v-structures are also considered as the core of d-separation (Def. 2) property. In the first path, A is an ancestor of B, but A doesn't impact B directly. It is similar in the second path, where B causes A indirectly. In the third path, both A and B are parents of vertex C, however, $B \notin adj(A, G)$ (or $A \notin adj(B, G)$). C is called $collider$ in this case [3]. There is no connection between A and

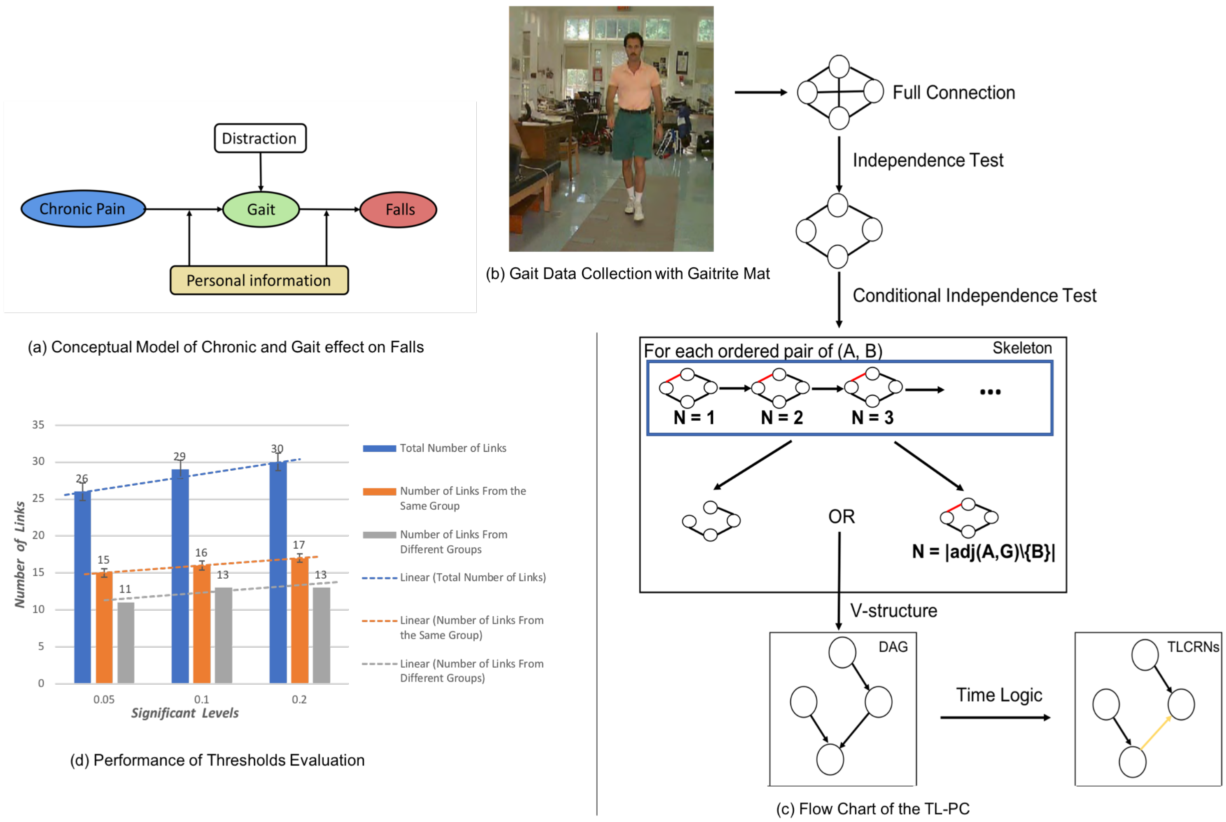

Fig. 1. **(a) Our conceptual model of chronic pain and gait effect on falls:** To investigate the relationships among these three groups, the distraction is added to create different conditions of walking. And the basic personal information of participants may affect both relationships of Pain-Gait or Gait-Falls. **(b) Our data collection experiment:** The picture shows how to collect gait data using the Gaitrite mat. For each kind of simulated walking type, participants are asked to walk through the mat twice. **(c)The flow chart of TL-PC Algorithm:** The algorithm begins with a full connection, and the conditional independence test is used to test the red edge after passing normal independence test. There are two ways to break the iteration, removing the red link or traversing all N. In this figure, we use the first situation to break the iteration and go to next step. **(d) Our theoretical threshold:** There is no significant difference between each threshold. The trend line shows the stabilization of the number of links, including total links, links between different groups and links between the same groups

B. In addition, the forth path shows that C is the common cause of A and B. Therefore, given C, there must be a relationship between A and B since their common ancestor. All three cases, except the third path, performs the causal connection between vertex A and B given C, so A and B are d-connecting given C. While, no causal connection can be found in the third path, in this case, A and B are d-separated by C. The definition of d-connection and d-separation are given below (Dif. 2).

Definition 2. ***D-Separation [3], [5], [6]:*** *In a DAG, vertex A and B are d-separated by a set of vertices C if there is a path between A and B, any non-collider on the path is not in C, or any collider and its descendant are not in C. Otherwise, vertex A and B is* ***d-connecting*** *by C.*

The TL-PC algorithm (the same as PC in step one) starts with the full connected graph, then for each vertex A testing the conditional independence of each connection of vertex B in $adj(A,G) \setminus \{B\}$, where $\forall$ A, B $\in$ V. We will use the normal independent test to all pair of vertices and remove irrelevant links first. And then applying the CI test to learn the skeleton (Algorithm 1). The CI test will be iterated by different vertices and levels (n) [3]. At the original level (n=0), normal independence test is used for pairwise vertices. Then at the first level (n=1), for the all possible subset C of $adj(A,G) \setminus \{B\}$, if it is d-separated then remove the independent edges. The number of member (size) of subset C equals to n. For example, when n=0, there is no variable in the subset C, so we run independent test instead of the conditional independent test since there is no conditional factors. The iteration will be terminated when the number of $adj(A,G) \setminus \{B\}$ is less than the level's number. If the number of required conditional variables (n) is greater than all linked variables in DAG, in this case, the algorithm is broken.

The second step of TL-PC is to orient all edges that survive from Algorithm 1. We use a set R to record an ordered pair of variables which represents the directed edges. The ordered pair of vertices (A, B) belong to set R if we have $A \rightarrow B$. If a vertex C connects with both vertices A and B respectively, but A and B are not adjacent, we can decide the direction as $A \rightarrow C \leftarrow B$, if A and B are d-connecting given C. It is easier to decide this collider structure since it is the only direction

Algorithm 1 Learning the Skeleton from CI Test

Input: Data set D with V variables and the significant level α
Output: Undirected graph G with V variables and E edges
Connect all vertices (A, B) V*V
Set n=0
for each pair of (A, B)2G **do**
  Test $I(A, B)$
if $I(A, B)$ **then**
  Remove the edge between A and B
  Update G and E
for each ordered pair of adjacent (A, B)2G **do**
  Set n=1
  repeat
    if SIZE (adj(A,G)nfBg) ⩾n **then**
      for each subset C adj(A, G)nfBg **do**
        if SIZE (C) = n **then**
          Test CI(A, BjC)
          if (A, B) is d-separated by S **then**
            Remove the edge between A and B
            Save C in Sepset(A,B) & Sepset(B,A)
            Update G and E
            Break
    n=n+1
  until SIZE (adj(A, G)nfBg) ⩽ n

if we know A ? B but A and B are not independent given C [4]. However, for non-collider vertices, it is hard to decide the direction since there are three different v-structures satisfied the result from the CI test.

After orienting collider vertices by using v-structure, the original PC propose two rules to deal with other edges in G based on the previous DAG [4]. First, if there is a directed path from A to B (it could include other vertices in the path), and B 2 adj(A, G), we orient the edge between A and B as A ! B. Second, if A directs to C and there is a link between C and B, meanwhile, A and B are separated, the edge between C and B can be oriented as C ! B. On the other hand, since the result is DAG, there are two more rules, 1)it is impossible to get any directed cycles in G, 2)no more v-structure should be formed. It is possible that some of the edges cannot be oriented by these rules. We propose to apply time logic to G. With this technique, some uncertain direction will be directed and some unsure direction will be revised.

Definition 3. ***Time Logic Causal Relationship:*** *A relationship between two phenomena is time logic if the cause independent phenomenon happening precedes the effect dependent phenomenon in time.*

In general, if a phenomenon (A) could cause another one (B), we call A has the causal effect on B, or we say the A is the reason of B. For example, considering an education case, the credits of one student leads to whether he/she can graduate. We say the credits have the causal influence on graduation.

The Gaussian conditional independent test is applied to diagnose the causal relationships, but the direction of relationships is decided by v-structure in DAG. However, with the real-world relations, the v-structure method is not considered as powerful as people's brain to address all complex relationships. It is easy to find a way to decide the direction of a cause-effect relationship from domain knowledge or common sense. But the core of this task is to find the causal relations, which is much more difficult than the direction. Therefore, after obtaining the causal relationships from PC, we implement the time logic relationship rule (Def. 3) to the original DAG and update the direction of part of edges in G. Every node in G has a happened time t, where t2T. According to t, we can revise the DAG by time logic rule.

With the time logic rule, the phenomenon previously happened only can be the efficiency factor of other later phenomena. Again, considering the example of graduation and credit grading, if the algorithm shows the direction like from graduation to the credits of a student, obviously, it is against the time logic relationship rule. Students cannot graduate before he/she is graded since grading must happen before graduation. In this case, based on the time logic, the only possible direction is from credits to graduation [7]. The newly generated time logic causal relationship networks (TLCRNs) following the time logic shows better performance of interpretation and reliability. The second step of TL-PC is shown in Algorithm 2 which following the original PC [4] at the beginning.

Algorithm 2 Orientation of G from Algorithm 1

Input: Undirected graph G with V variables and E edges
Output: TLCRNs G with V variables and DE directed edges
for each triple vertices set A, B and C in G **do**
  if C2adj(A, G)nfBg & C2adj(B, G)nfAg
    & A2̸adj(B, G) & C2̸Sepset(A, B) **then**
    Save (A, C) and (B, C) in R
  Update G and DE
for each ordered pair of vertices (A, B) in G **do**
  if A sequence of ordered pair from A to B in R
    A2 adj(B, G) **then**
    Save (A, B) in R
  if (A, C) R & B2adj(C, G) & B2̸adj(A,G)nfCg **then**
    Save (C, B) in R
Update G and DE
for each ordered pair of vertices (A, B) R;
  t_A, t_B 2 the set of time T **do**
  if $t_A > t_B$ **then**
    Remove (A, B) from R, and save (B,A) in R
Update G and DE

III. Real-world Application on Older Adult Falls

From previous research, chronic multisite pain is a potential influence factor of falling in older population [8]–[10]. Chronic multisite pain is one of the most common disabling conditions affecting older adults. Although pain may have different origins and presentations, it causes significant inconvenience and limited mobility for senior people. Furthermore, falling is not only impacting older people's quality of life but also is one of the most important causes of death among older people [11]. Fall-induced injuries may cause death directly, such as head injuries, and also may cause serious complications. These complications usually happen if the participant is bedridden as a result of the fracture, such as bedsore. In this case, it is necessary to find the influence factors which cause a high risk of falling in older persons.

Our study is designed to detect the relationship between chronic pain and falls in the older population, both of which are highly prevalent in older people. People did not recognize chronic pain as an important factor of falls in older adults until 2002 [12]. More recently, population-based research in the general population of older adults showed risk for falls related to pain, regardless of how pain was assessed [13]. Interestingly, there is no evidence showing that a specific single location of pain would increase falling risk. For example, lower body pain was not observed to confer more risk than upper body pain. However, as in the example about smoking and alcohol, correlative variables do not always have causation. Although previous studies find the correlative relationship between pain and falls, understanding the causal relationship is essential and would be very helpful in multi-factorial fall prevention.

We propose applying machine learning techniques to detect the real networks of pain and falls. Examining pain variables and falling variables is not sufficient since falling only happens when people are upright. If we directly test the relationship between chronic pain and falls, the influence of factors performed during walking would be ignored. To solve this problem, we consider adding gait parameters to describe how people walk and also add variables about their personal information. We believe these "assistant" variables are able to help us to discover authentic causal relations between pain and falls. In addition, the results of our experiments, due to the design of the TL-PC framework, are visible and easily understood.

A. Data Set Description

Our study participants are 203 women and 111 men aged from 71 years to 101 years in the MOBILIZE Boston Study II. The experiment covers all these 314 people, and each of them walked on the Gaitrite mat 6 times. Although some of records are missing, we have 1857 sample walks (27 missing records). There are 23 features in the Older Adult Falls data set. The details and explanation are in Fig. 2.

The dataset contains 13 gait features, 1 distraction feature, 4 personal information features, 3 pain features, and 2 fall features. Fall features refer to TOTFY (total follow-up years) and TOTFalls (total number of falls). In the period of TOTFY, participants would be investigated monthly and the number of falls would be recorded cumulatively. The TOTFY of each participant is varied. For example, one participant is tracked for 4.33 years, whereas another participant is followed

Older Adult Fall Data Set	
TOTFY	Total years were tracked
TOTFalls	Total number of falls in the experiment span
Walk_Type	Three different distraction types
Step_TimeL/R	The duration of the same foot (L for left and R for right) completing single step in the gait cycle
Step_LenL/R	The length of the same foot (L for left and R for right) completing single step in the gait cycle
Stance_TimeL/R	The duration of the stance phase of left and right foot in the gait cycle.
Swing_TimeL/R	The time of swing phase during the gait cycle
BPIsev_Tert	A ranked score of pain severity
BPIinterf_Tert	A ranked score of pain interference
Age	The age when he/she joined the experiment
Race_Grp	The race of the patient
PainWHAS3	A measure of number of sites of pain
Edu_Grp	The ranked education level of he/she
Gender	The gender of patients
DblSupp_TimeL/R	The time of both feet in contact with floor
Stride_TimeL/R	The duration of completing one stride for left or right foot
Gait_Spd	The time it takes to walk through the GAITRite mat

Pain features
Personal Information features
Gait features
Fall features
Distraction features

Fig. 2. The Description of Data Set (L and R represent two individual variables, so there are 23 variables in total)

only 1.82 years. Personal Information features include each participant's profile, representing individuals' characteristics and specific circumstances from different perspectives. Gait features describe how the participants walk. We use the Gaitrite mat and wearable sensors to collect 13 gait features from (see Fig. 1(b)). Distraction feature describes 3 walk types: quiet walk, dual tasks easy and dual tasks hard, which are expressed as 0, 1 and 2 to simulate peoples daily gait status in different situations. The quiet walk is walking without any distraction. Participants only focus on walking in this case. For the dual tasks, participants walk with a low or high degree of cognitive distraction. We ask each participant to count backward from 100 by 1 for the easy dual tasks and count backward by 3 for the hard task. Pain features describe how the participants feel pain and the sites of pain. Among them, chronic pain assessment and gait measure are needed to be described in the details. We used a questionnaire within 13 items about joint pain to assess chronic musculoskeletal pain in hands shoulders, back, chest, wrists, knees, hips, and feet [14]. This measurement appoach was used in the Womens Health and Aging Study [17], [18]. Gait measure were divided into 2 conditions: single task walking and dual tasks with a challenge to cognitive attention. To do the gait testing, we used a GaitRite mat(CIR Systems Inc, Havertown PA) with pressure sensors inserted and distributed. Previously, the Gaitrite mat performed dependably for most spatiotemporal gait parameters in older people [15]. The mat was 16-foot long and 3-feet wide, and measured the characteristics and timing of individual steps. Then we used these variables to calculate spatio-temporal gait parameters: stride length, stride time and swing time, which are necessary for the outcome measures of variability. The calculation of these parameters is based on the individual gait cycle, from the time when one foot touches the floor until the same foot touches the floor again. The stride length is the distance of one complete gait cycle; the stride time refers to the timing of a complete gait cycle, and swing time is the amount of time that the foot is in the air for each step (secs). These gait measures have been verified and used in gait assessment research previously [16].

B. Specific Targets

In the past two decades, there are a lot of researchers investigating the role of mobility and balance in fall risk in older adults. Obviously, balance has a strong relationship with falls since if people lose balance they would fall. In this case, we believe mobility, at least, will be an influential factor of falls. That is why we measured gait features, which could describe the mobility of persons. On the other hand, chronic pain is a factor which imposes restrictions on walking [19]. Limited mobility causes different ways of walking, as well as gait, and then leads to different levels of falling risk. Therefore, gait was considered as a bridge connecting two interesting appearances, falls and chronic pain. Our primary target in this paper is providing a way which can build a precise pathway between chronic pain and falls.

We designed to test the sequential conditional independence between falls and chronic pain. As the flow chart shown in figure 1(a), gait is an underlying influence factor of the relationship between pain and falls. In this case, gait data was collected to test whether the relation of gait and other two groups of features exists in older adults. In general, our specific targets are the following.

- **The relationships between Pain and Gait:** To investigate whether chronic pain results in different performances in gait variables.
- **The relationships between Pain and Falls:** To investigate whether chronic pain results in different performances in the occurrence of falls.
- **The relationships between Gait and Falls:** To investigate whether different performances in gait lead to increased variability in the risk of falls.

IV. EXPERIMENTS

In this section, we present the experiment results from our application to older adult falls. We provide both interpretable directed causal relationship network and numeric possible total causal effects to support the explanations in a real-world related task. In particular, we illustrate the core relationships between variables in the task. All three specific targets (the causal relations of Pain-Gait, Pain-Falls, and Gait-Falls, respectively) are discussed and evaluated from both the technical and domain view.

A. Experiment Setup

From data collection, we, totally, have 23 features (Fig. 2) in the Older Adults Falls data set. We use all of these features but apply some pre-processing to prepare data. We generate a normalized variable, Fall_Rate, which is from TOTFalls and TOTFY using Eq.2.

$$Fall\_Rate = TOTFalls \quad TOTFY \tag{2}$$

In this case,regardless of the starting point and missing point of each individual in the older Adults Falls study, all information behind observed value is converted into only one powerful feature.

One of the primary goals of our task is providing a readable result to all researchers with or without strong academic training in statistics. To reduce the quantities of features can extremely increase the performance of an explanation. However, to pursue the degree of precision, as more as valued features should be considered in the model. It is tough to find an appropriate balance between these two opposite challenges. In order to address this, we utilize average values to replace all gait features except Gait_Spd which is only one kept as original. All other 6 gait features (including Step_Time, Step_Len, Stance_Time, Swing_Time, DblSupp_Time, and Stride_Time) are measured with the left foot and right foot, respectively. So in the original data set, there are 12 features, such as Step_TimeL and Step_TimeR etc. For instance, instead of Step_TimeL and Step_R, We propose to use one feature, Step_Time_ave (average), which can represent the entire body movement. In general, there is no significant difference between the performance of individual foot and the whole body in gait recognition. On the other hand, in statistics, equalization is one of the most important technique to realize the measure of central tendency of a probability distribution. This procedure makes the data farther follow the Gaussian distribution which is similar with the population (extremely big data) distribution in the real world.

B. Time Logic in Older Adults Fall Program

In our Older Adults Falls data set, there are five different groups of variables (Fig. 2). It is worth noting that the group of personal information (PI) contains all default profile variables for the participants in our data collection step. For example, the gender of participants is considered a fixed variable, having occured before our experiment. So, every change of independent variables in the PI group should happen before participants join our experiments. As all causal effects determined by our experiments must follow the time order rule, the only reliable direction is from PI to all other groups since default variables always occur at the very beginning.

Moreover, we record falls after all data collection processing, which leads the variable Fall_Rate to be the last effect dependent variable. All activities of data collection precede the investigation of falls in time. So Fall_Rate only can perform the role of the result of variables from other groups, such as pain, gait, and distraction. Another interesting group following the time order rule is the group of distraction. This group is designed and controlled by researchers when they collect gait data. In this way, distraction must be the cause of variables from gait group. But there is no influence on other groups.

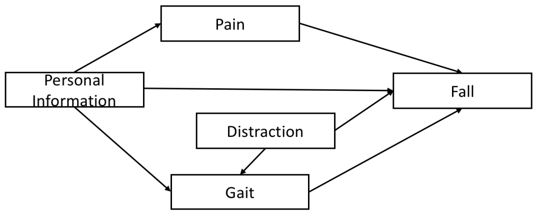

Fig. 3. The Possible Time Logic in Groups

Otherwise, we cannot detect more time order relationships between the 5 groups. It could be any direction of the causal relationships among these groups. Every event can happen before or after another one, which means it can be the cause of result of any other variables.

All possible time order relationships are shown in Fig. 3 where the direction of arrows represents the time-order-based causal effects. Variables without links mean that there could be any kind of relationship in the pair.

C. Dynamic Performance of Relations

In the experiments, we generate the time logic causal relationship networks plot based on the Gaussian conditional independence test. To evaluate the stability of relations, we set the significance level for the tests (α in the algorithm) in a sequence of 0.05, 0.1 and 0.2. As in Fig. 1(d), there is no significant difference shown under different thresholds. Only a few distinctions can be detected among the results with different thresholds. In this case, we marked the changes with each confidential interval, which clearly performs the dynamic relations.

We generate the Time Logic Causal Relationship Networks (TLCRNs) using the TL-PC algorithm. The TLCRNs (Fig. 4) covers 16 variables, including 7 gait variables, 1 distraction variable, 1 fall variable, 4 gait variables and 3 pain variables.

As usual in traditional statistics, we chose a 95% significance level as the base level and increase the threshold to observe dynamic performance (Fig. 4). Different colour and line types are used to identify the weaker causal relationships with a higher threshold. With a high significant level, we can find strong relations. As shown in Figure 1(d), there is no link that disappears when increasing the threshold, while, only a few new links are added. Since the relationship is steady, it is reliable for researchers. However, investigating the dynamic changes of the TLCRNs can help researchers find supported features which have the strong relationship with others. Furthermore, support variables increase the reliability and interpretability of the causal relationship.

In the Fig. 4, there are 4 weaker relations, which are PainWHAS3 ! Fall_Rate, Gender ! Fall_Rate, Age ! Gender, and Step_Time_ave ! Dblsupp_Timw_ave. Two weaker relations towards to the Fall_Rate. In this way, there are 5 causal relationships of Fall_Rate in total, and three of them are strong. PainWHAS3 is one of the weaker causal factors of Fall_Rate. It is in the same group as BPIinter_Tert

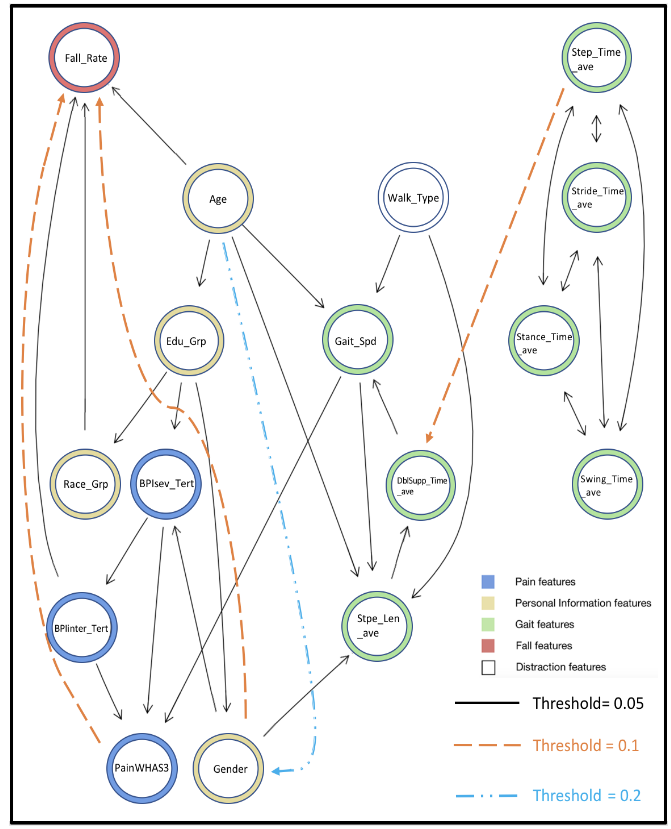

Fig. 4. The Time Logic Causal Relationship Networks (TLCRNs) Generated by the TL-PC Algorithm. Directed edge represents causal relations, while double arrows edge means uncertain direction.

which strongly affect Fall_Rate. From the TLCRNs, all three pain variables show the strong relationship in the group. So the weaker relation between PainWHAS3 and Fall_Rate supports the strong relationship in the same group. The same as Gender which is another weaker cause of Fall_Rate. We can find strong causal relationships between Race, Age, and Fall_Rate, respectively. Gender is from the same group as these two variables. The weaker relations support the strong relations when we set a higher threshold, and we can detect a strong relationship between the weaker cause and strong cause coming from the same group.

There is another interesting weaker relationship between Step_Time_ave and DblSupp_Time_ave. We can only find this link after setting 0.1 or higher threshold. There are 4 isolated variables which are Step_Time_ave, Stride_Time_ave, Stance_Time_ave, and Swing_Time_ave respectively. The causal effects in the group of these 4 variables only can be detected in the group. In other words, the interactions of these 4 variables are independent of the rest 12 variables. Interestingly, all of these 4 isolated variables are relevant to the time of gait. So we believe that the information on gait time does not have strong causal effects on other variables. The weaker relation between Step_Time_ave and DblSupp_Time_ave also support this. The only one weaker relation is just connect two of the time variables.

D. Investigation of Specific Targets

In the experiment, we define all 16 variables into 5 different groups (Fig. 2). Variables in the same group always have strong and frequent interactions, since only the highest relative variables which represent the same characteristic will be put in the same group. However, in this section, we target to find the causal relationships between groups, especially for the specific targets of the application.

The relationships between Pain and Gait

There is only one strong direct causal relationship between Pain variables and Gait variables can be found from the TLCRNs (Fig. 4). Walking Speed (Gait_Spd) impacts the number of sites of pain (PainWHAS3) significantly. In this case, walking speed is the core variable which connects gait and pain.

The relationships between Pain and Falls

Fall_Rate is strongly influenced by the pain variable BPI-inter_Tert which is a scaled approach to describe the feeling of pain. Another weaker causal relationship is PainWHAS3 ! Fall_Rate. Obviously, there are very robust relationships between 3 pain variables. So the weaker effect between pain and falls also supports that the performance of pain can impact the risk of falls.

The relationships between Gait and Falls

There is no direct influence between gait and falls, however, gait could be the indirect cause of falls. From the previous two relationships, walking speed strongly affects the number of pain positions, while, pain variables have a significant influence on the risk of falls.

From the experiment result, some important causal relationships among falls, gait and pain can be detected. Pain is considered as a strong cause of falls. Meanwhile, pain and gait have influence relation, which contributes to the indirect causal influence of gait to falls. Besides, we also find that the personal profile background performs a powerful influence on the risk of falls. Through these default features, researchers can filter out the group of participants with high risk of falls and provide more help.

V. Conclusion

The TL-PC algorithm successfully combines statistics independent test and machine learning data-driven approach. It is an efficient, visible and explainable method which can generate causal relationship networks based on Bayesian probability theory. The conditional independent test is used to investigate interactions among all variables. Furthermore, a more competitive and reliable technique, time logic, is implemented to orient the causal relationships.

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